

CC5212-1

PROCESAMIENTO MASIVO DE DATOS

OTOÑO 2021

Lecture 1

Introduction

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THE VALUE OF DATA

Soho, London, 1854

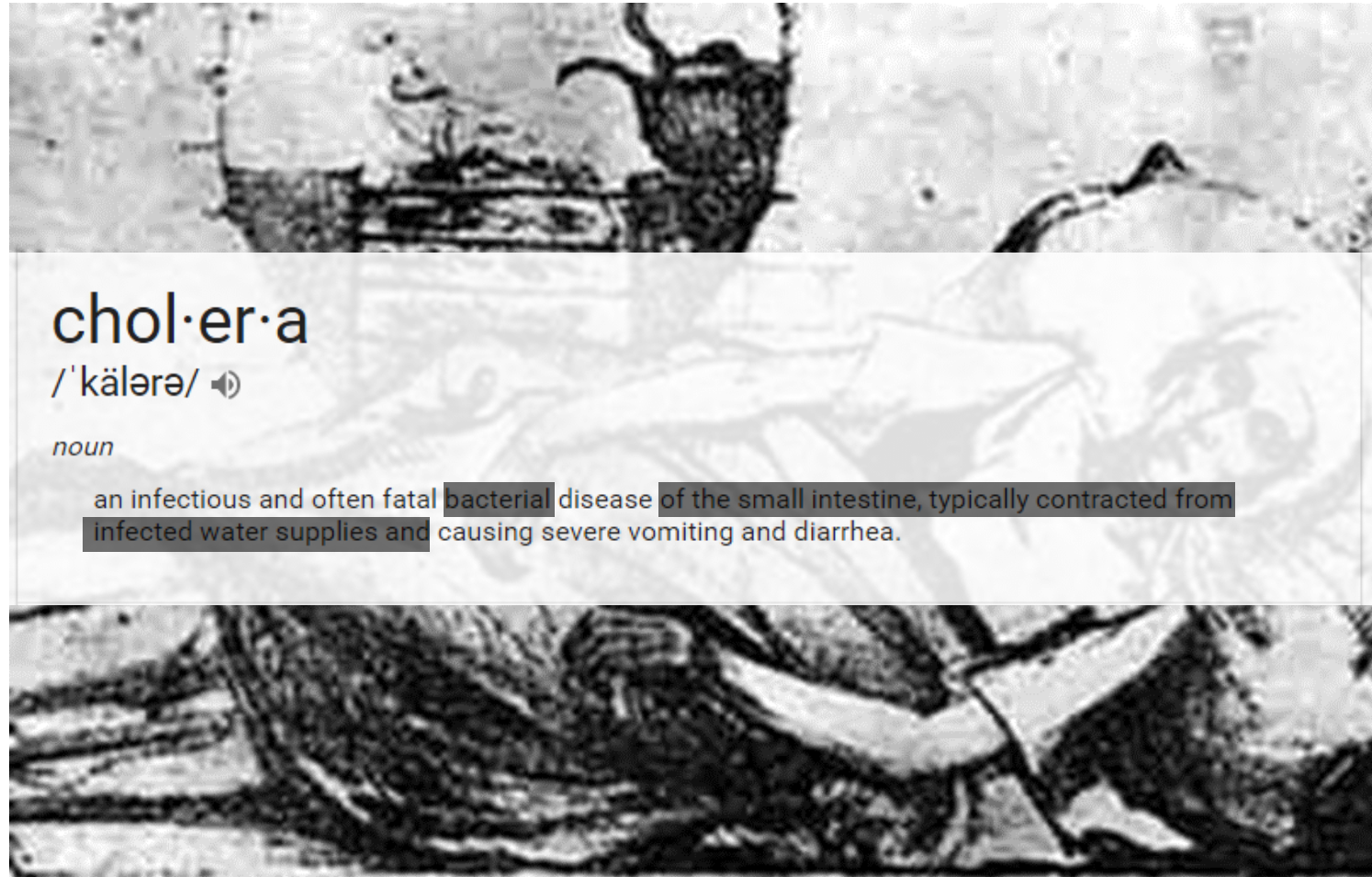


A COURT FOR KING CHOLERA.

Cholera: What we know now ...



Cholera: What we knew in 1854



chol·er·a

/ˈkælərə/ 

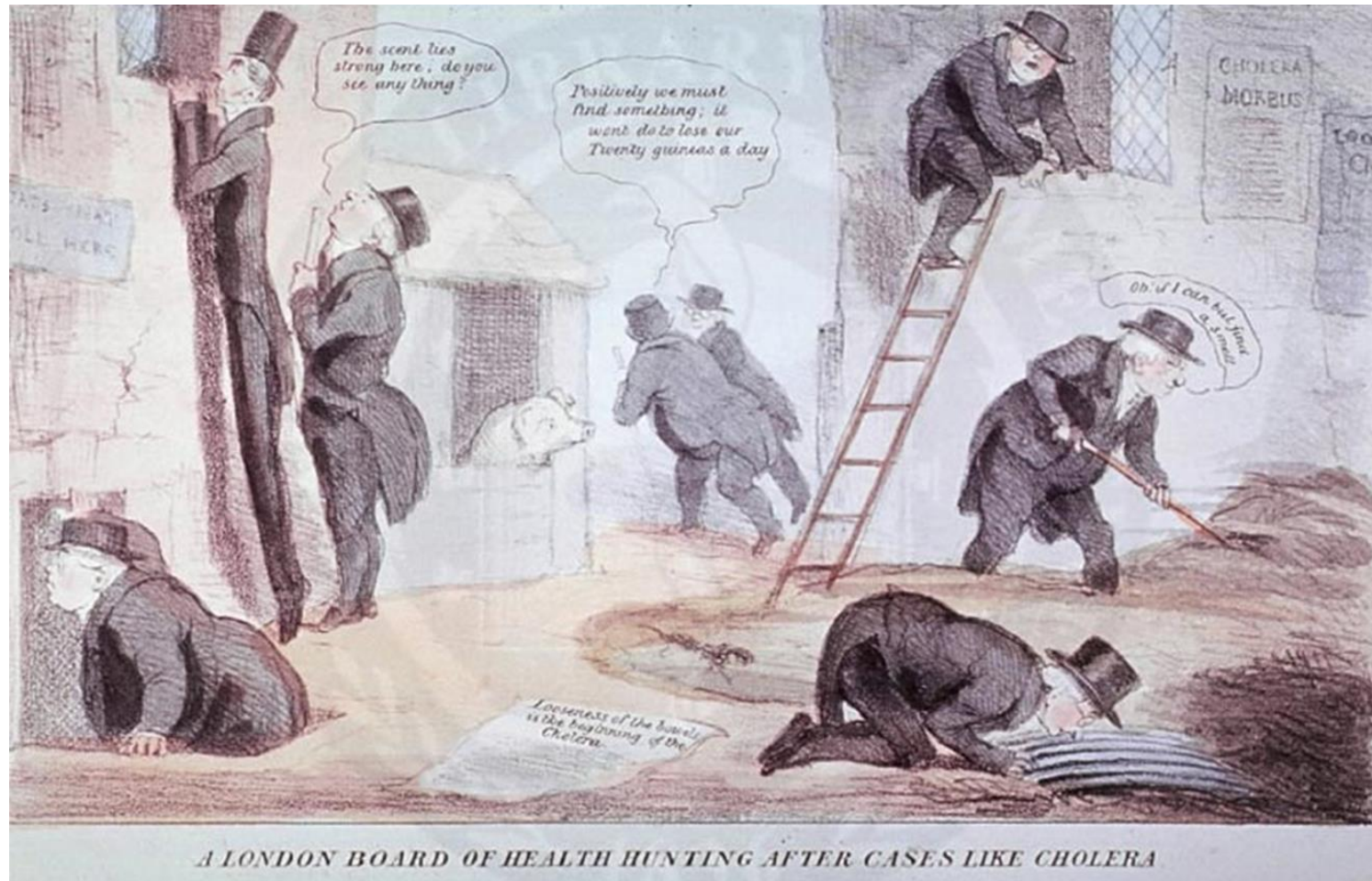
noun

an infectious and often fatal bacterial disease of the small intestine, typically contracted from infected water supplies and causing severe vomiting and diarrhea.

1854: Galen's miasma theory of cholera



1854: The hunt for the invisible cholera



John Snow: 1813–1858



John Snow: 1813–1858



The survey of Soho



The survey of Soho

Registration Districts.	Registration Sub-Districts.	Population in 1851.	Estimated population supplied with water as under.			Deaths from cholera in 1854.		Calculated mortality in the population, supplied with water as under.			
			Southwark and Vauxhall Co.	Lambeth Co.	Both Companies together.	Total deaths.	Deaths per 10,000 living.	Southwark and Vauxhall Co. at 160 per 10,000.	Lambeth Co. at 27 per 10,000.	The two Companies.	Calculated deaths per 10,000 supplied by the two Companies.
St. Saviour, Southw.	1. Christchurch	10,022	2,015	13,234	16,149	113	71	46	36	82	57
	2. St. Saviour	10,700	10,337	898	17,235	378	192	201	2	203	153
St. Olave	1. St. Olave	8,015	8,745	0	8,745	161	201	140	0	140	160
	2. St. John, Horselydown	11,360	9,360	0	9,360	152	134	150	0	150	160
Bermondsey	1. St. James	18,899	23,173	603	23,866	362	192	370	2	372	156
	2. St. Mary Magdalen . .	13,934	17,258	0	17,258	247	177	276	0	276	160
	3. Leather Market . . .	15,205	14,003	1,092	15,095	237	155	224	3	227	150
St. George, Southw.	1. Kent Road	18,126	12,630	3,997	16,627	177	98	202	11	213	134
	2. Borough Road . . .	15,862	8,937	6,672	15,609	271	171	143	18	161	104
	3. London Road	17,830	2,872	11,497	14,369	95	53	46	31	79	55
Newington	1. Trinity	20,922	10,132	8,370	18,502	211	101	162	22	184	99
	2. St. Peter, Walworth .	29,861	14,274	10,724	24,998	391	131	228	29	257	103
	3. St. Mary	14,033	2,983	5,484	8,467	92	66	48	15	63	74

CHOLERA AND THE WATER SUPPLY

What the data showed ...



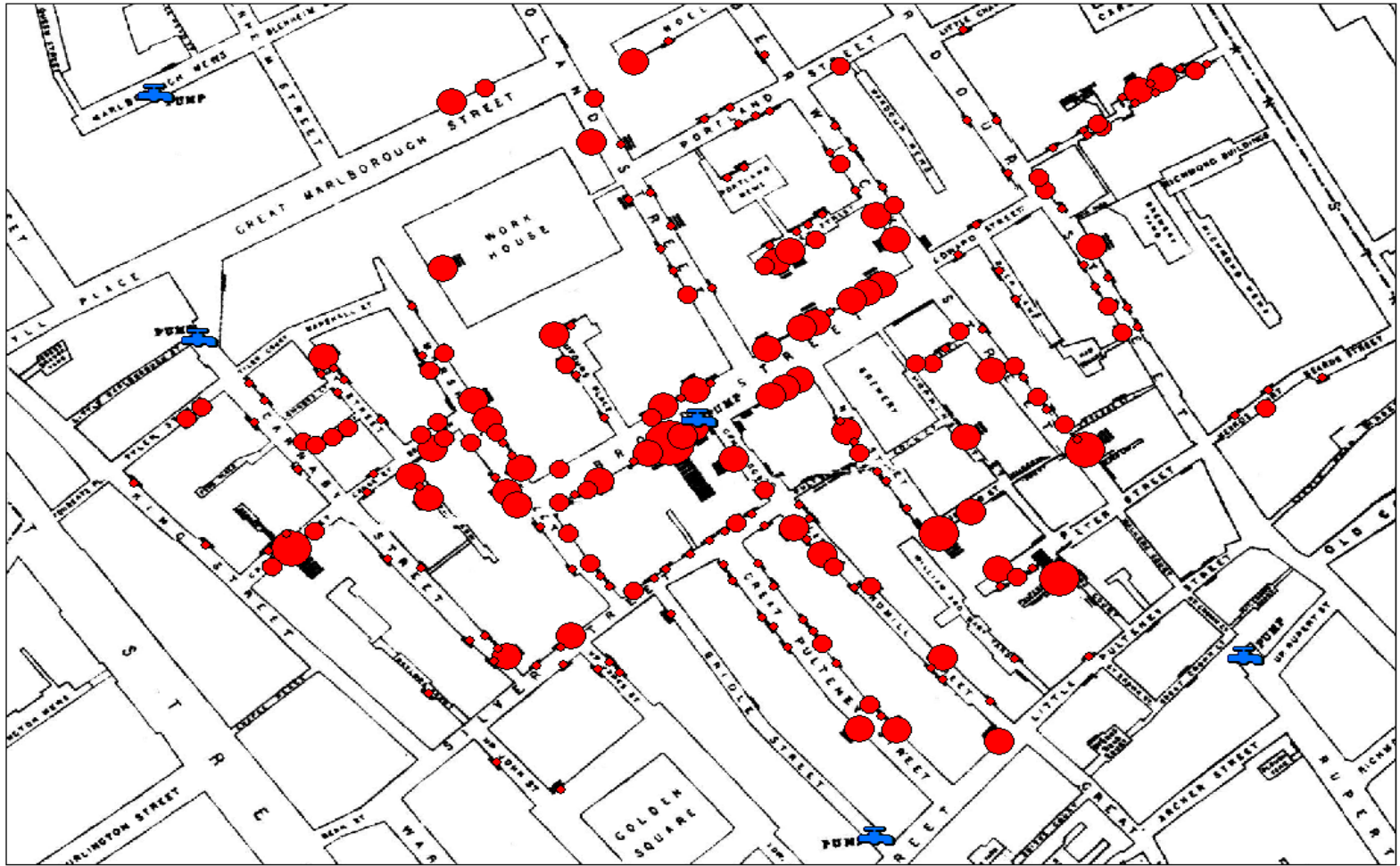
the from cholera
in 1854.

Total deaths	Deaths per 10,000 living
--------------	-----------------------------

113	71
378	192
161	201
152	134
362	192
247	177
237	155
177	98
271	171
55	53
211	101
391	131
02	66



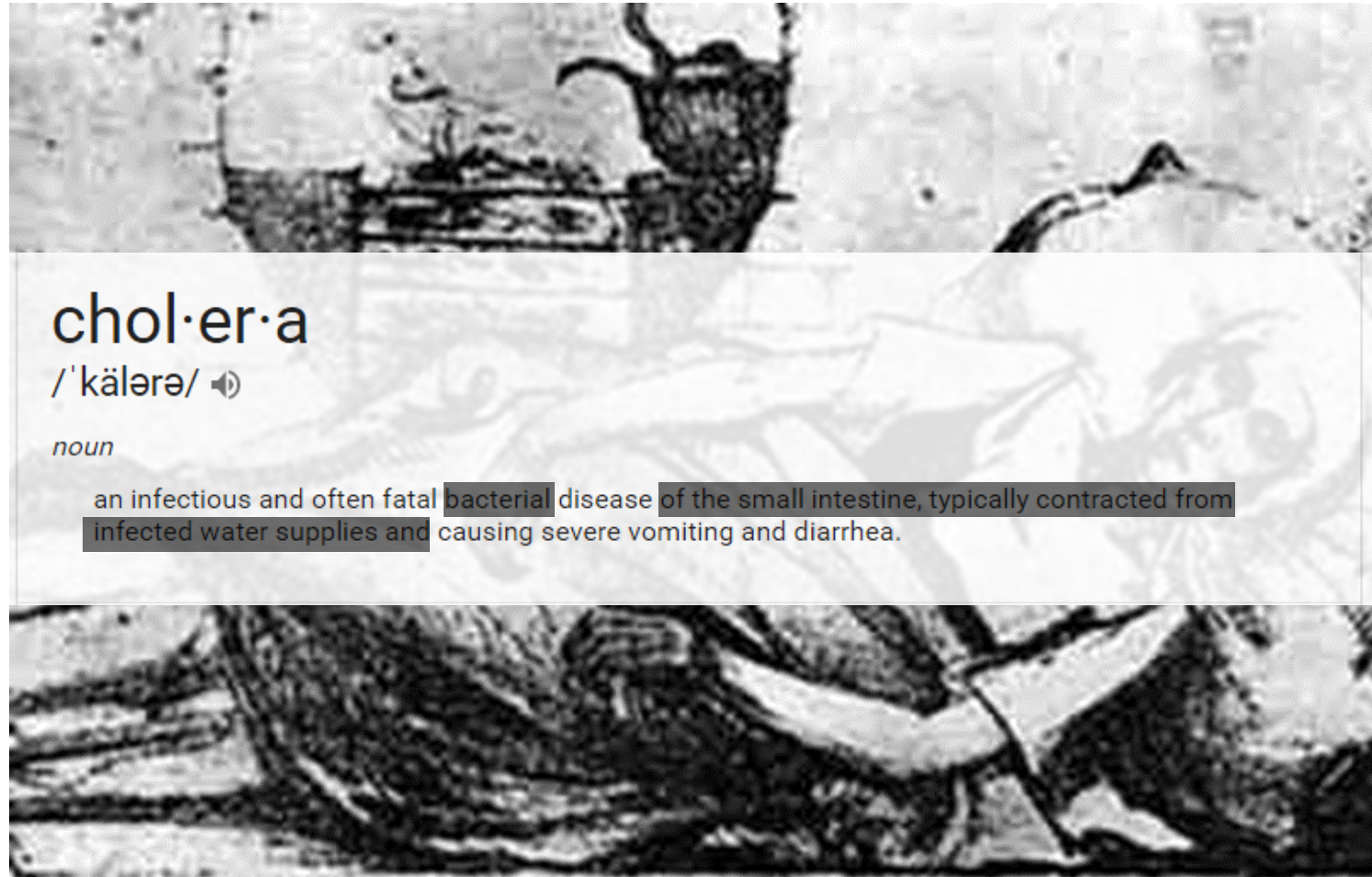
What the data showed ...



616 deaths, 8 days later ...



Cholera: What we knew in 1855



chol·er·a

/ˈkælərə/ 

noun

an infectious and often fatal bacterial disease of the small intestine, typically contracted from infected water supplies and causing severe vomiting and diarrhea.

Cholera boil notice ca. 1866

CHOLERA
AND
WATER.
BOARD OF WORKS
FOR THE LIMEHOUSE DISTRICT,
Comprising Limehouse, Ratcliff, Shadwell,
and Wapping.

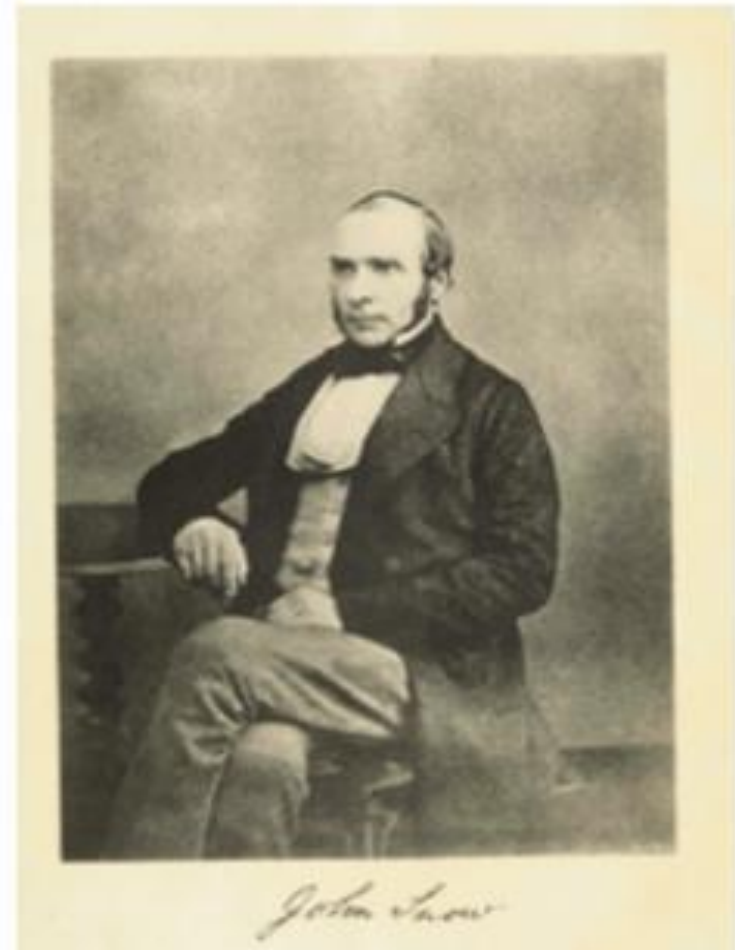
The INHABITANTS of the District within
which **CHOLERA IS PREVAILING**, are
earnestly advised

NOT TO DRINK ANY WATER
WHICH HAS NOT
PREVIOUSLY BEEN BOILED.

Fresh Water ought to be Boiled every
Morning for the day's use, and what
remains of it ought to be thrown away
at night. The Water ought not to stand
where any kind of dirt can get into it,
and great care ought to be given to see
that Water Butts and Cisterns are free
from dirt.

BY ORDER,
THOS. W. RATCLIFF,
CLERK OF THE BOARD.

Board Office, White Horse Street,
1st August 1866.



Cholera boil notice ca. 1866

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AND
WATER.
BOARD OF WORKS
FOR THE LIMEHOUSE DISTRICT,
Comprising Limehouse, Ratcliff, Shadwell,
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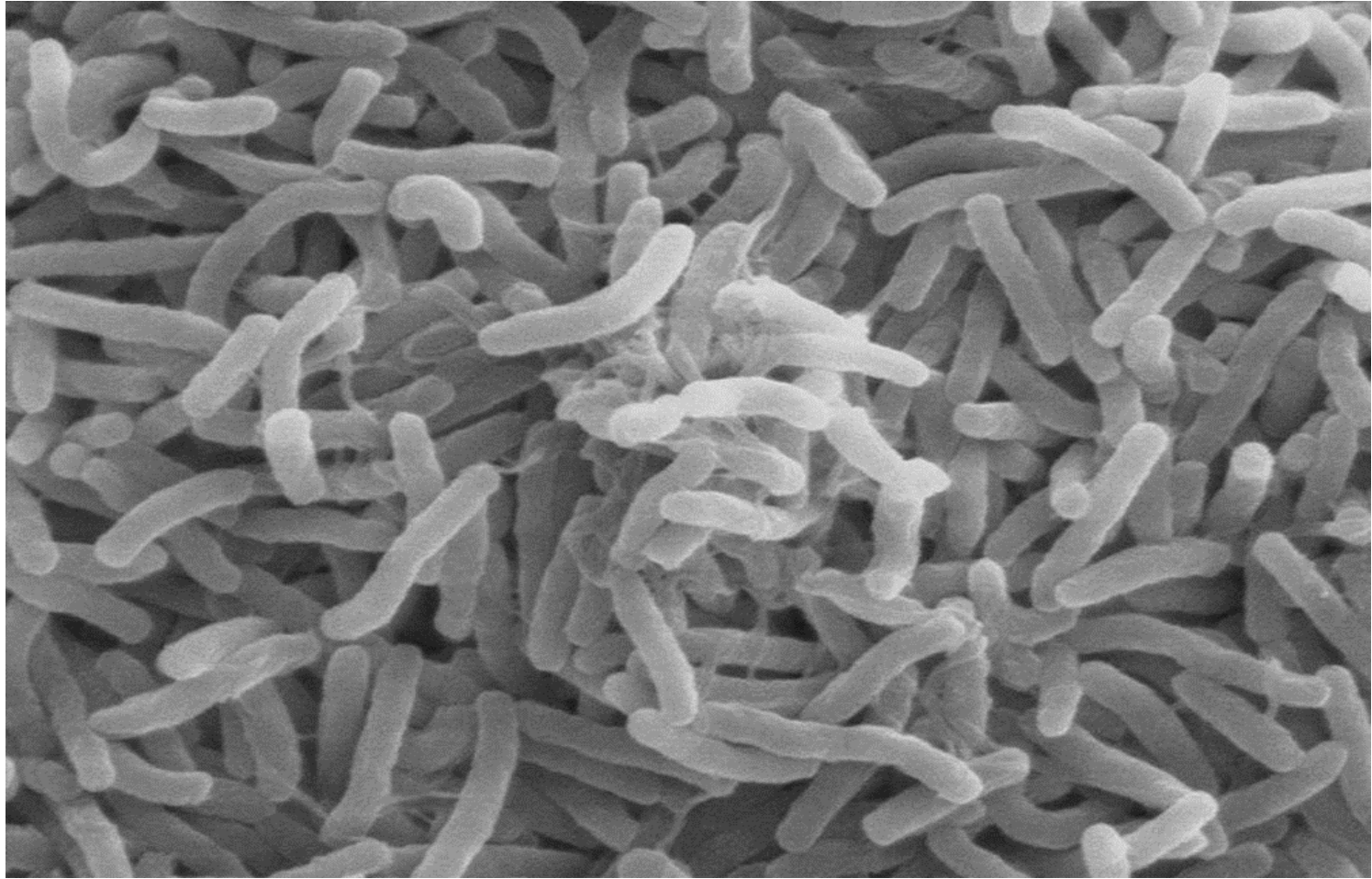
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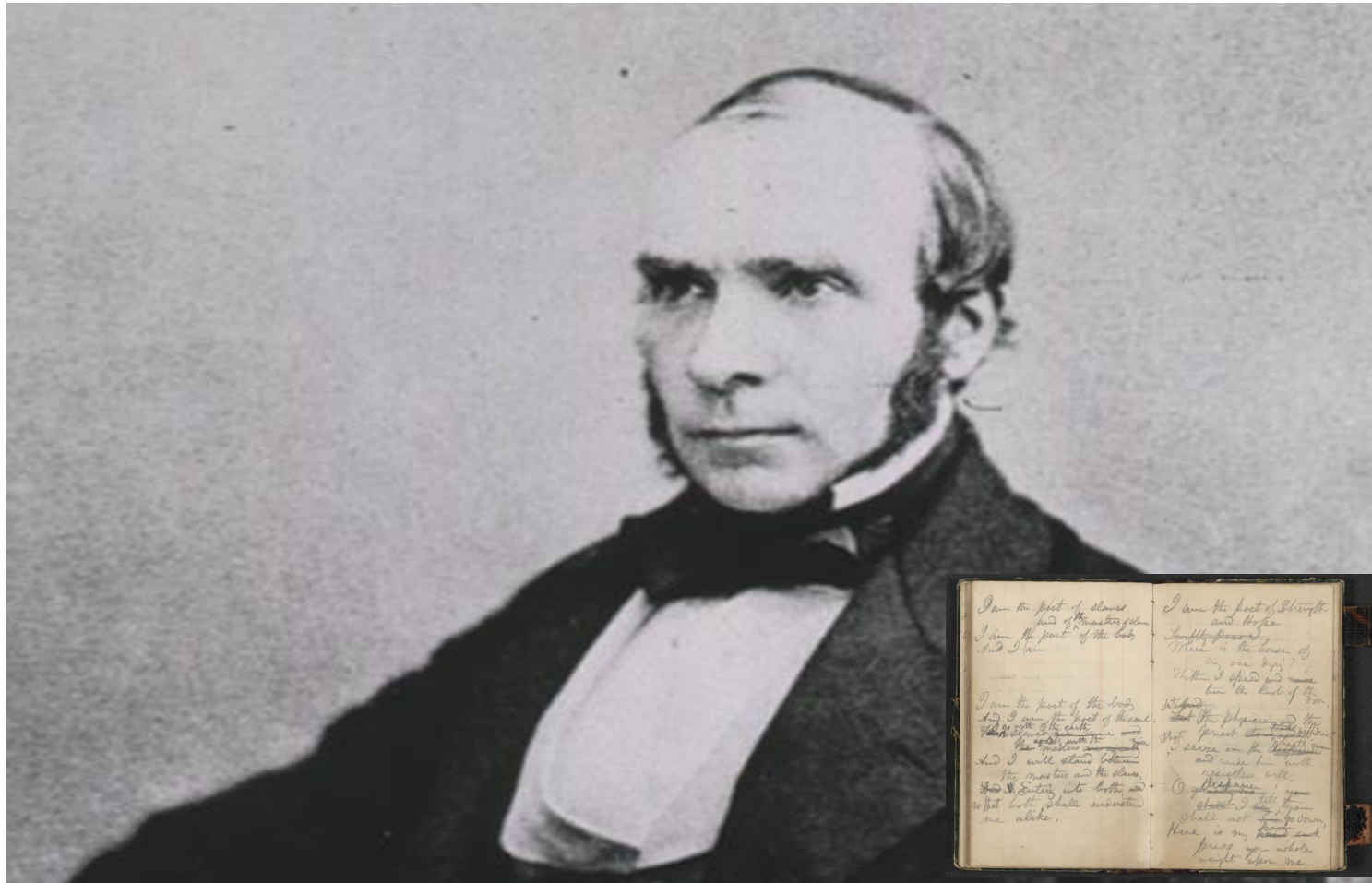
Board Office, White Horse Street,
1st August 1866.



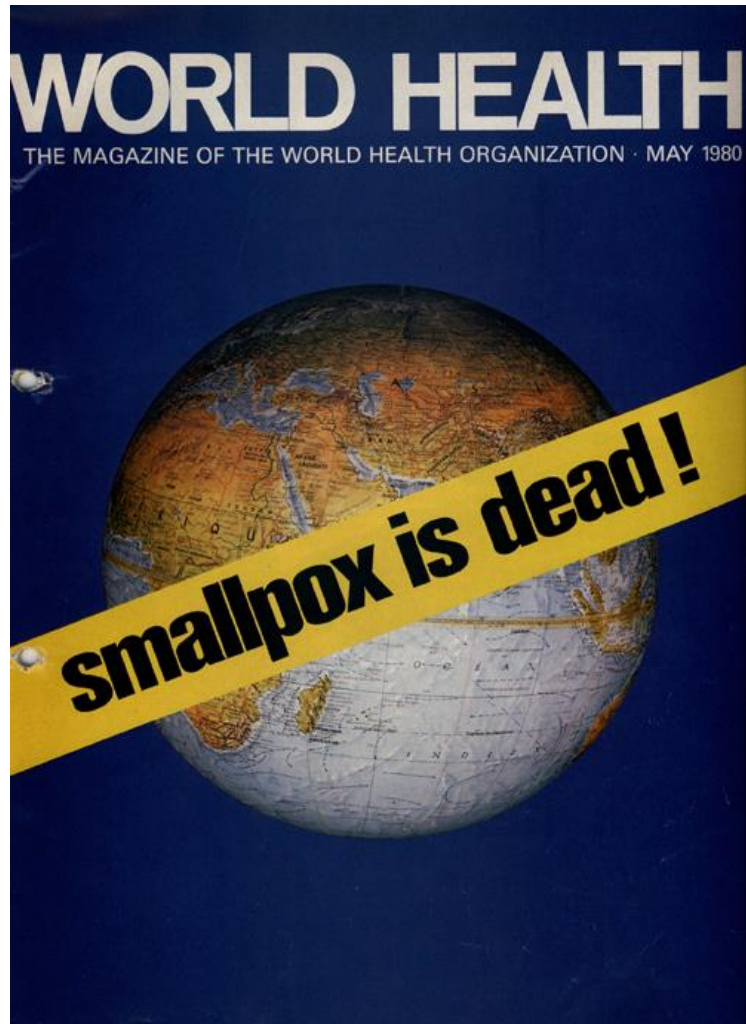
Thirty years before discovery of *V. cholerae*



John Snow: Father of Epidemiology



Epidemiology's Success Stories

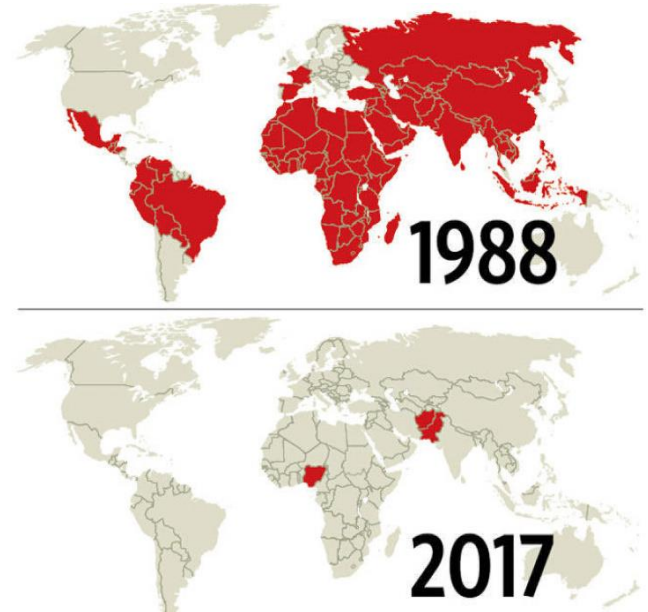


The polio endgame

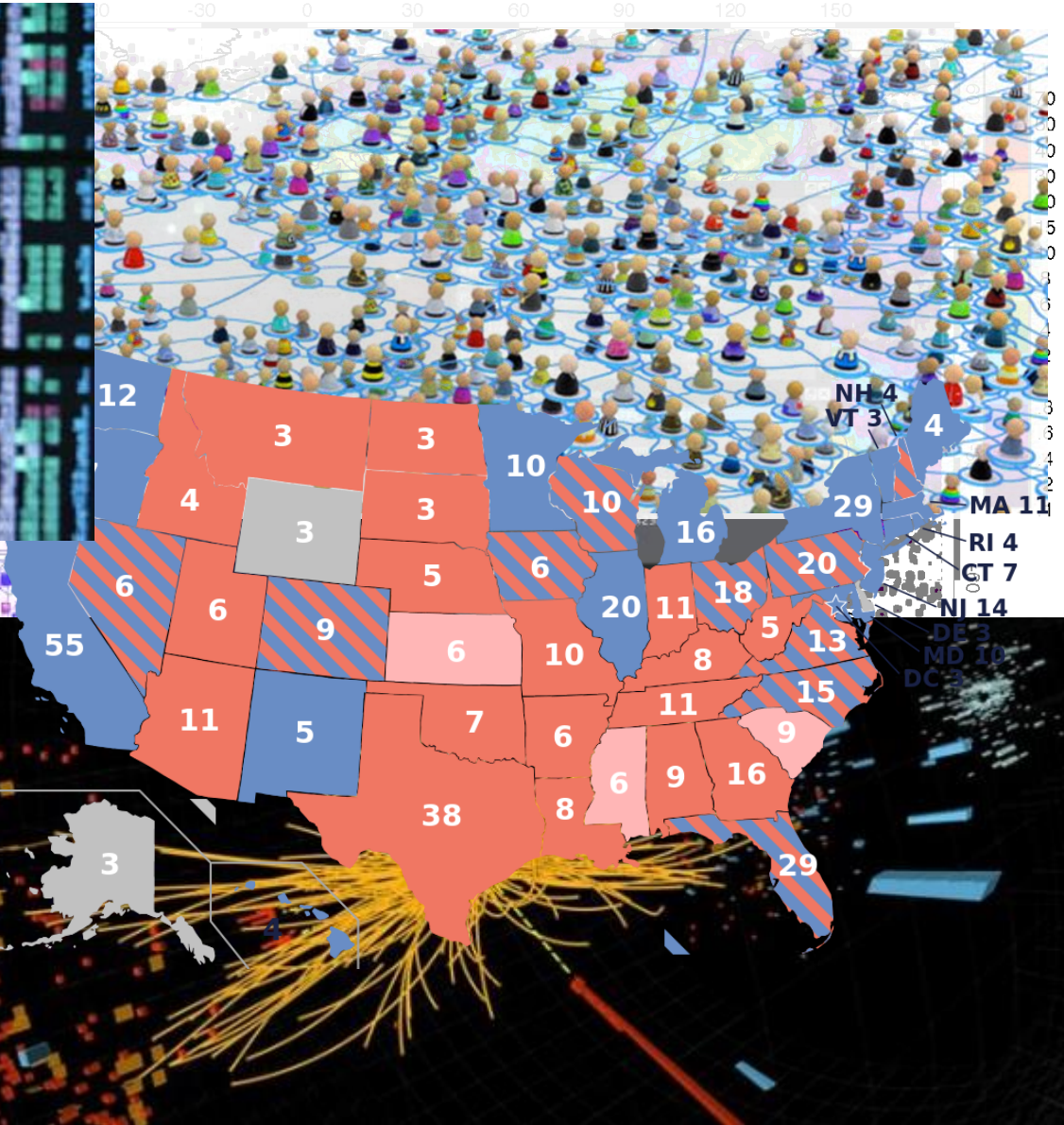
Since 1988, when the WHO resolved to eradicate polio, its footprint has shrunk dramatically. It is only considered endemic in Afghanistan, Pakistan and Nigeria (which hasn't seen a case since 2016). Last year there were only 22 new cases reported.

	1988	2017
■ Endemic countries	125	3

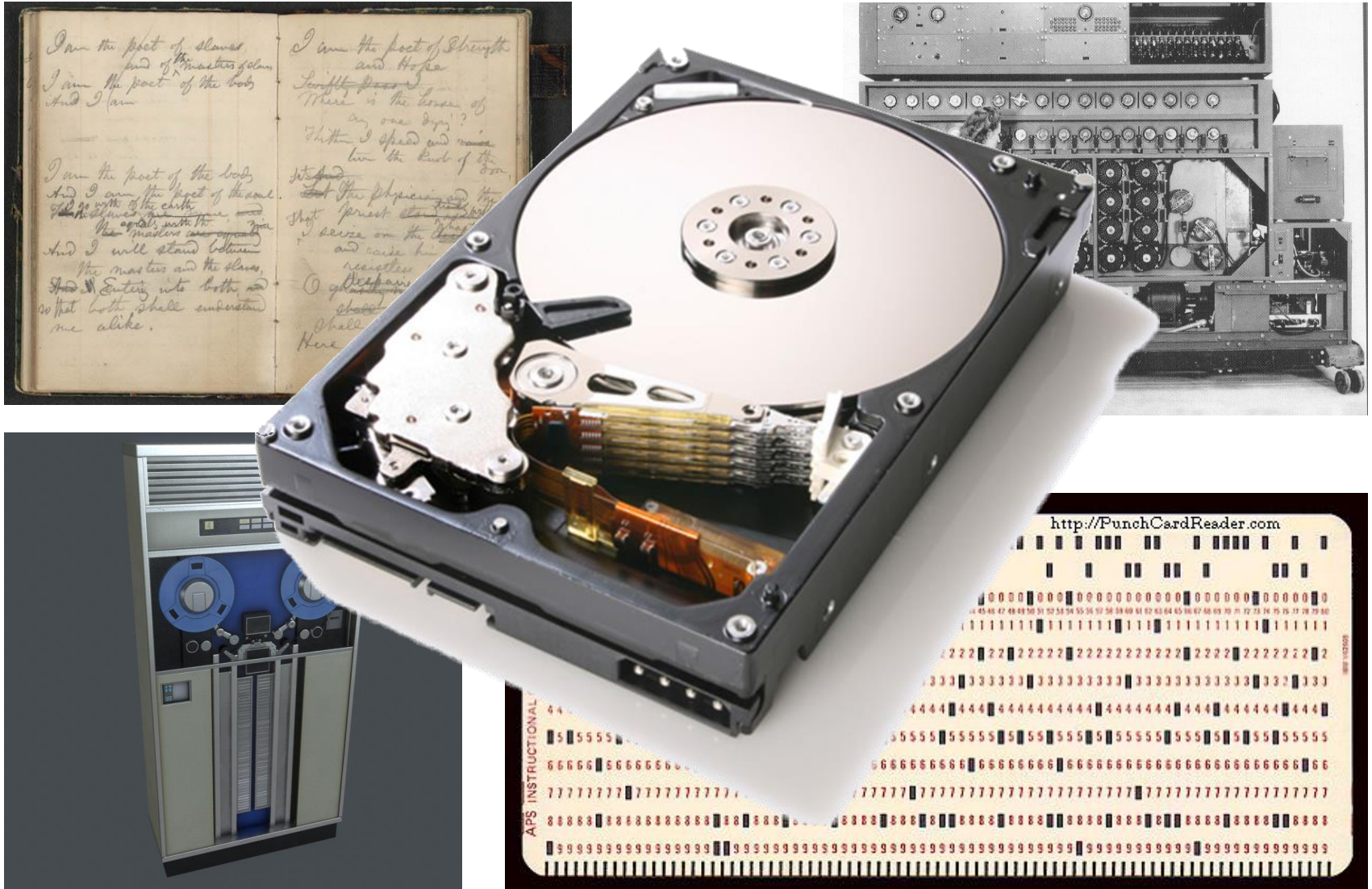
SOURCE: World Health Organization
TORONTO STAR GRAPHIC



The collage consists of four distinct images. The top-left image shows a person from behind, looking at a wall of server racks with glowing lights. The top-right image is a large, dense network graph with many nodes and connections. The bottom-left image is a complex 3D visualization, possibly a game environment or a data visualization, with a grid and various elements. The bottom-right image is a map of the United States with states colored in red, blue, and grey, and a large yellow starburst graphic.



(Paper) Notebooks no longer good enough



THE GROWTH OF DATA

“Big Data”



English Wikipedia

≈ 51 GB of data

(2015 dump)

(Text; No edit history)

(XML, uncompressed)

WIKIPEDIA
The Free Encyclopedia

1 Wiki = 1 Wikipedia

“Big Data”



Wikimedia Commons

≈ 24 TB of data

≈ 470.6 Wiki

(2014 dump)



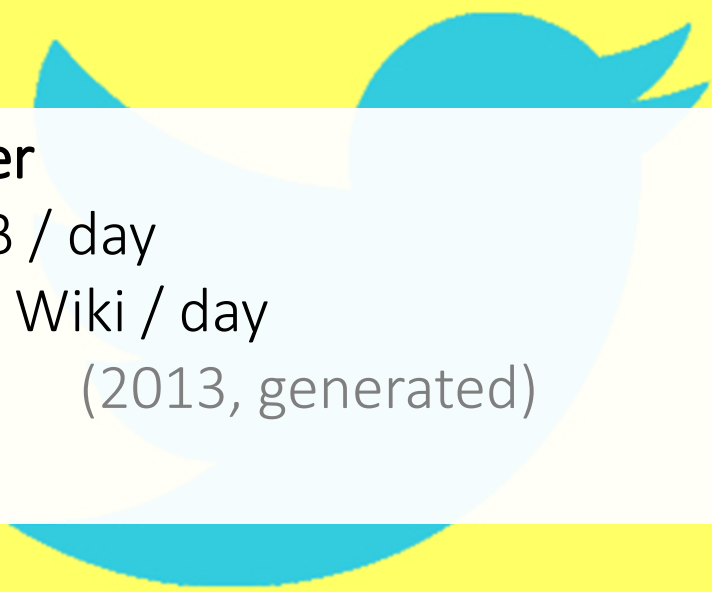
“Big Data”

Twitter

≈ 8 TB / day

≈ 157 Wiki / day

(2013, generated)



twitter

“Big Data”



Large Synoptic Survey Telescope

≈ 15 TB / day (night)

≈ 294 Wiki / day

(2020, generated)



“Big Data”

Facebook

≈ 600 TB / day

≈ 11,764 Wiki / day

(2014, incoming Hive data)



The more of your data I gather,
the more I understand
what it means
to be *human*.

“Big Data”



Large Hadron Collider

$\approx 1 \text{ PB / day}$

$\approx 19,607 \text{ Wiki / day}$

(2017, filtered data)



“Big Data”

PRISM: NSA Surveillance

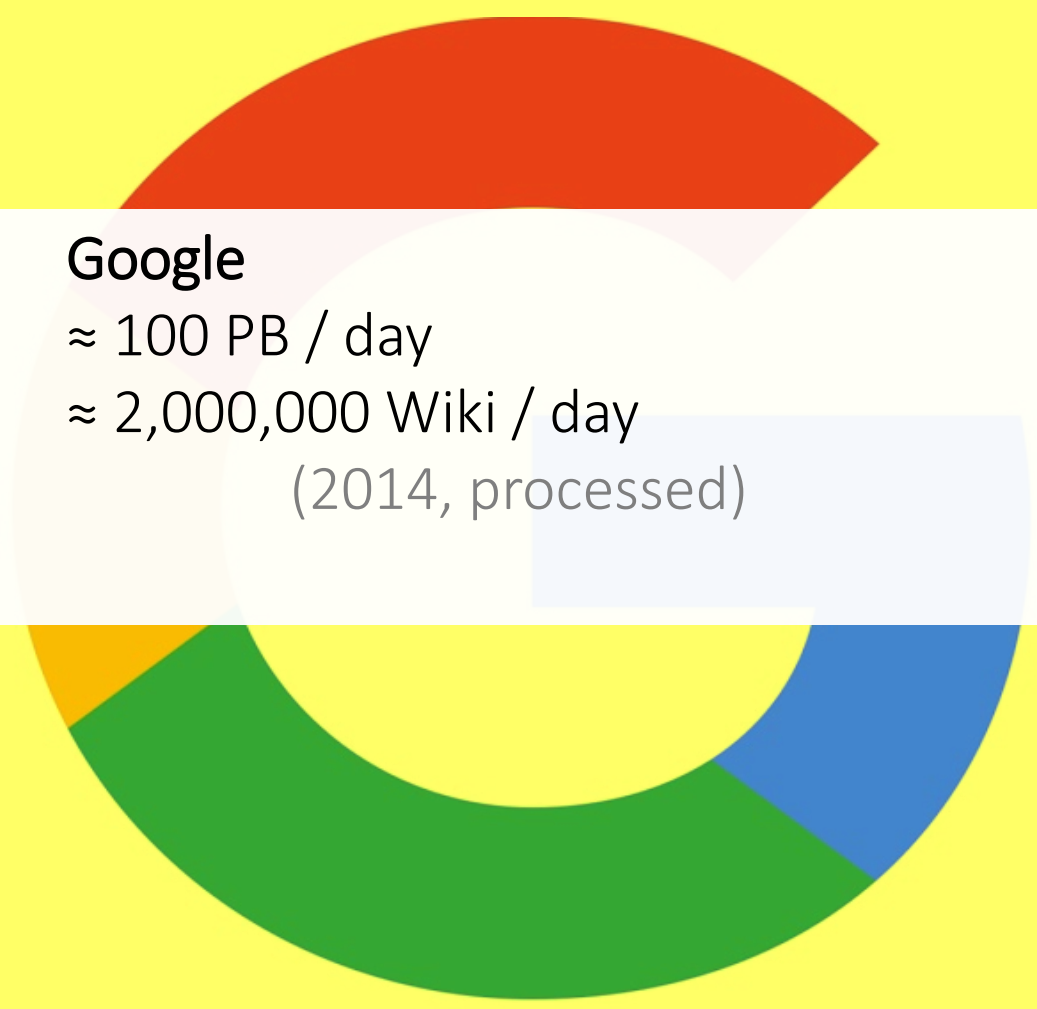
≈ 29 PB / day

≈ 568,627 Wiki / day

(2013, processed)



“Big Data”



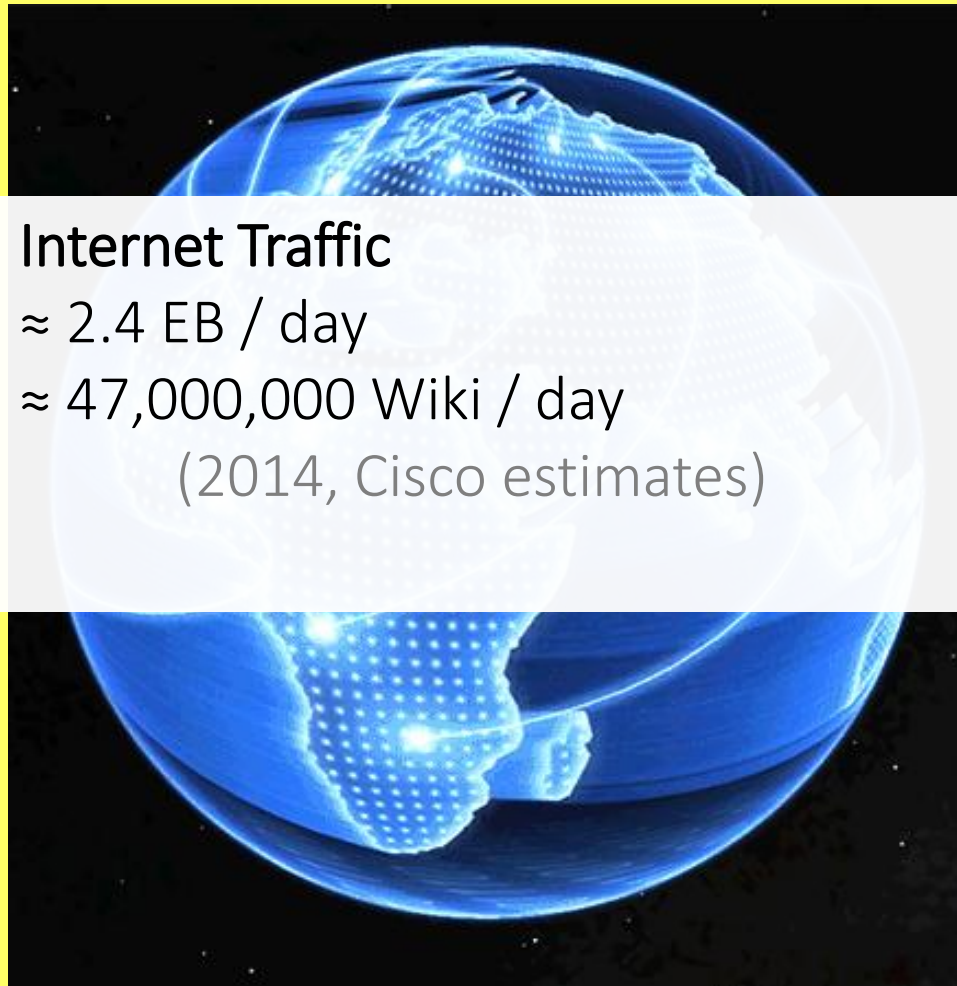
Google

≈ 100 PB / day

≈ 2,000,000 Wiki / day

(2014, processed)

“Big Data”



Internet Traffic

≈ 2.4 EB / day

≈ 47,000,000 Wiki / day

(2014, Cisco estimates)

Data: A Modern-day Bottleneck?



The 'V's of "Big Data"

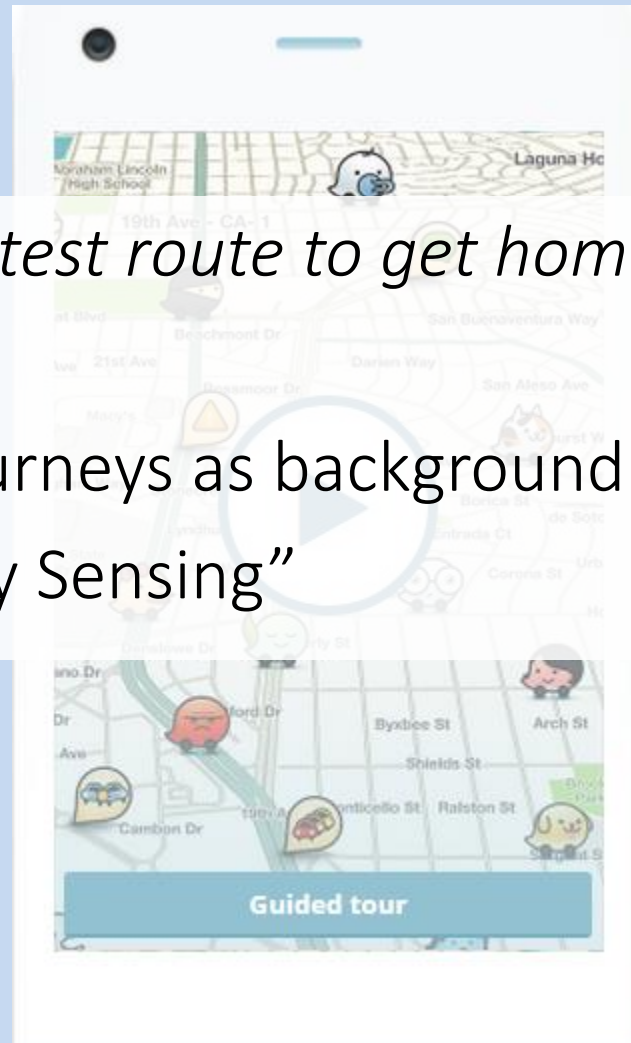


“BIG DATA” IN ACTION ...

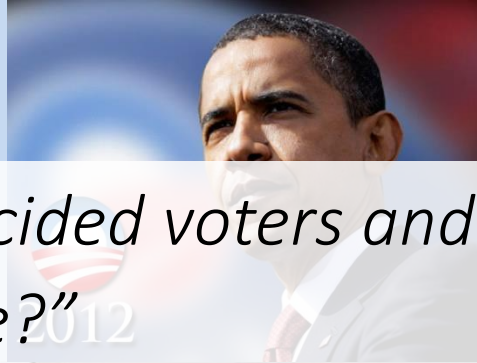
Getting Home (Waze)

“What’s the fastest route to get home right now?”

- Processes journeys as background knowledge
- “Participatory Sensing”

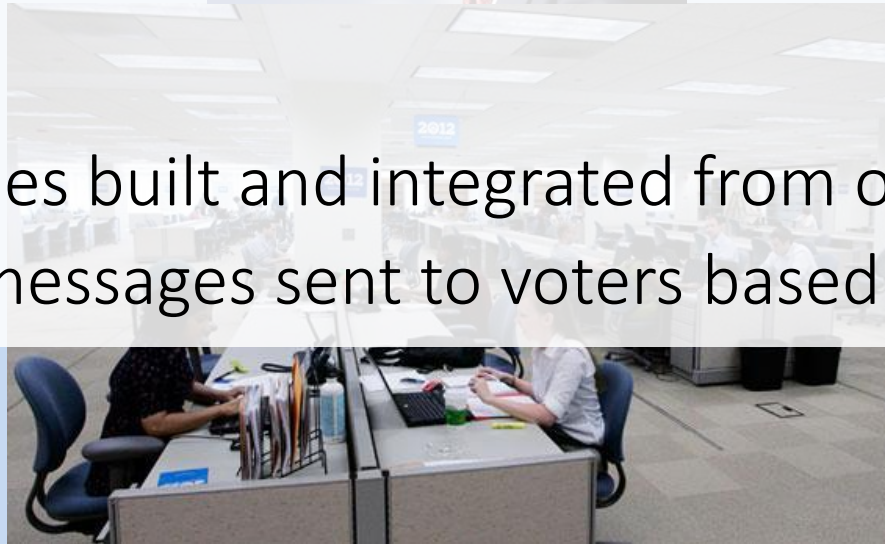


Getting Elected President (Narwhal)



“Who are the undecided voters and how can I convince them to vote for me?”¹²

- User profiles built and integrated from online sources
- Targeted messages sent to voters based on profile



Getting Elected President (Narwhal)



“Who are the undecided voters and how can I convince them to vote for me?”²⁰¹²

- Us
- Ta



facebook

Winning Jeopardy (IBM Watson)

“Can a computer beat human experts at Jeopardy?”

- Indexed 200 million pages of content
- An ensemble of 100 processing techniques

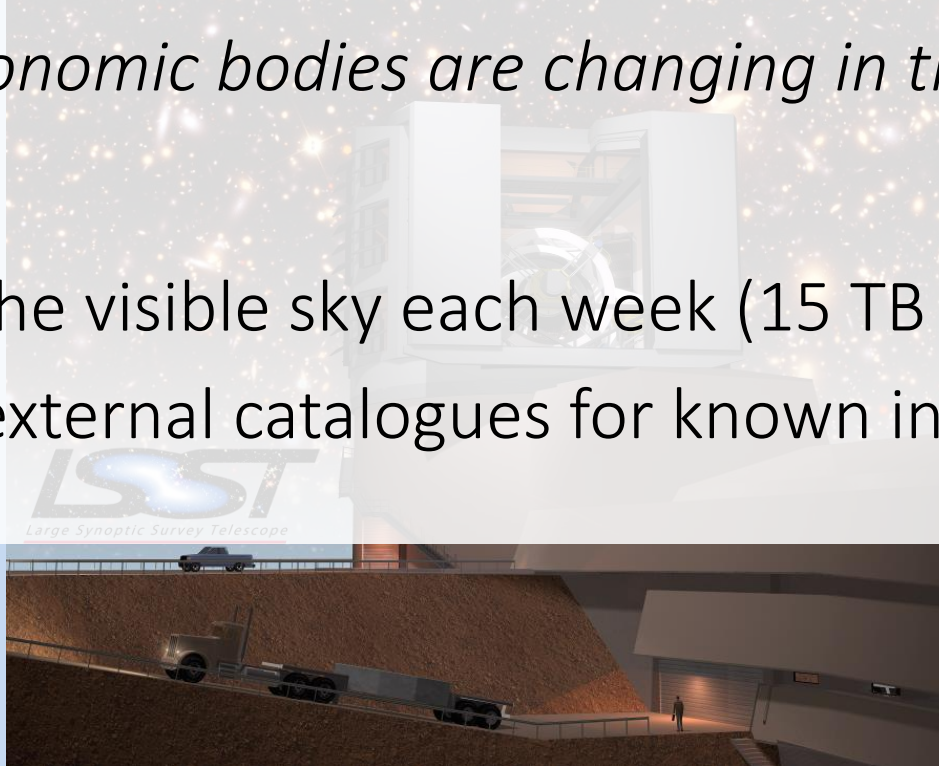


Surveying the Night Sky (LSST)



“What astronomic bodies are changing in the sky?”

- Surveys the visible sky each week (15 TB / day)
- Queries external catalogues for known information



PROCESSING LOTS OF DATA ...

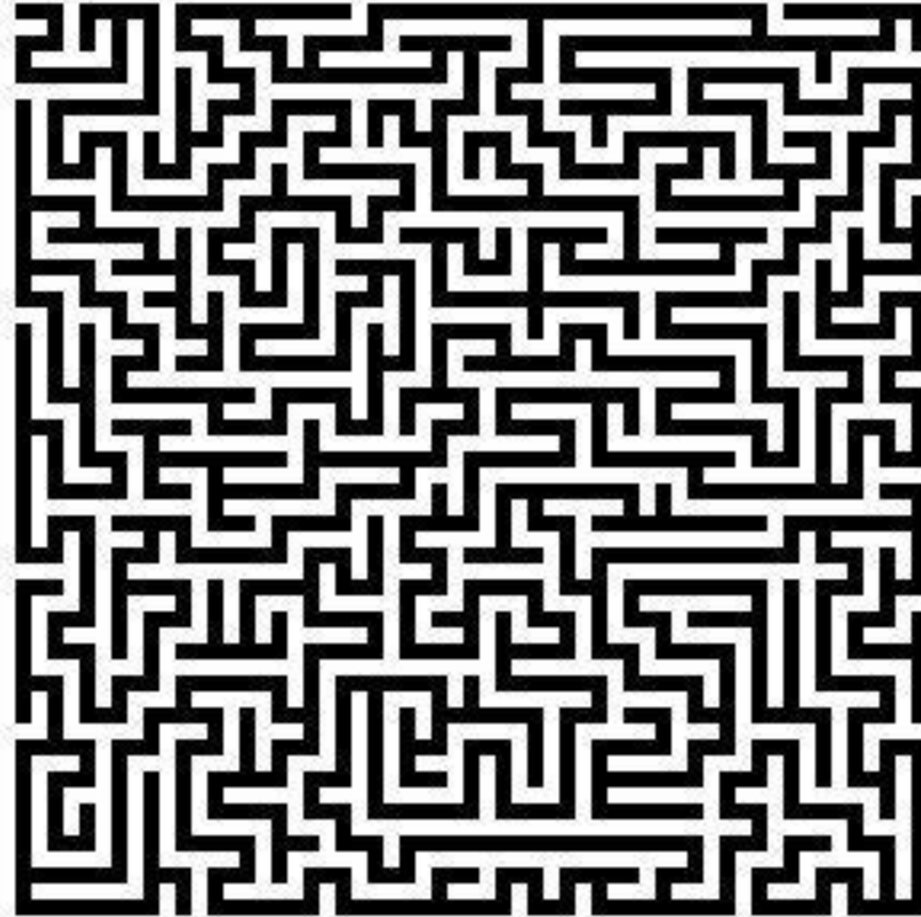
Every Application is Different ...

- **Data** can be
 - (Semi-)Structured data
 - (Relational DBs, JSON, XML, CSV, HTML form data)
 - Unstructured data
 - (text document, comments, tweets)
 - And everything in-between!

Every Application is Different ...

- **Processing** can involve:
 - Data Management
 - ([indexing](#), [querying](#), [joins](#), [aggregation](#))
 - Natural Language Processing
 - ([keyword search](#), [topic extraction](#), [entity recognition](#), [machine translation](#), etc.)
 - Data Mining and Statistics
 - ([pattern recognition](#), [classification](#), [regression](#), [recommendations](#), etc.)
 - Or something else / A mix

So where to start?



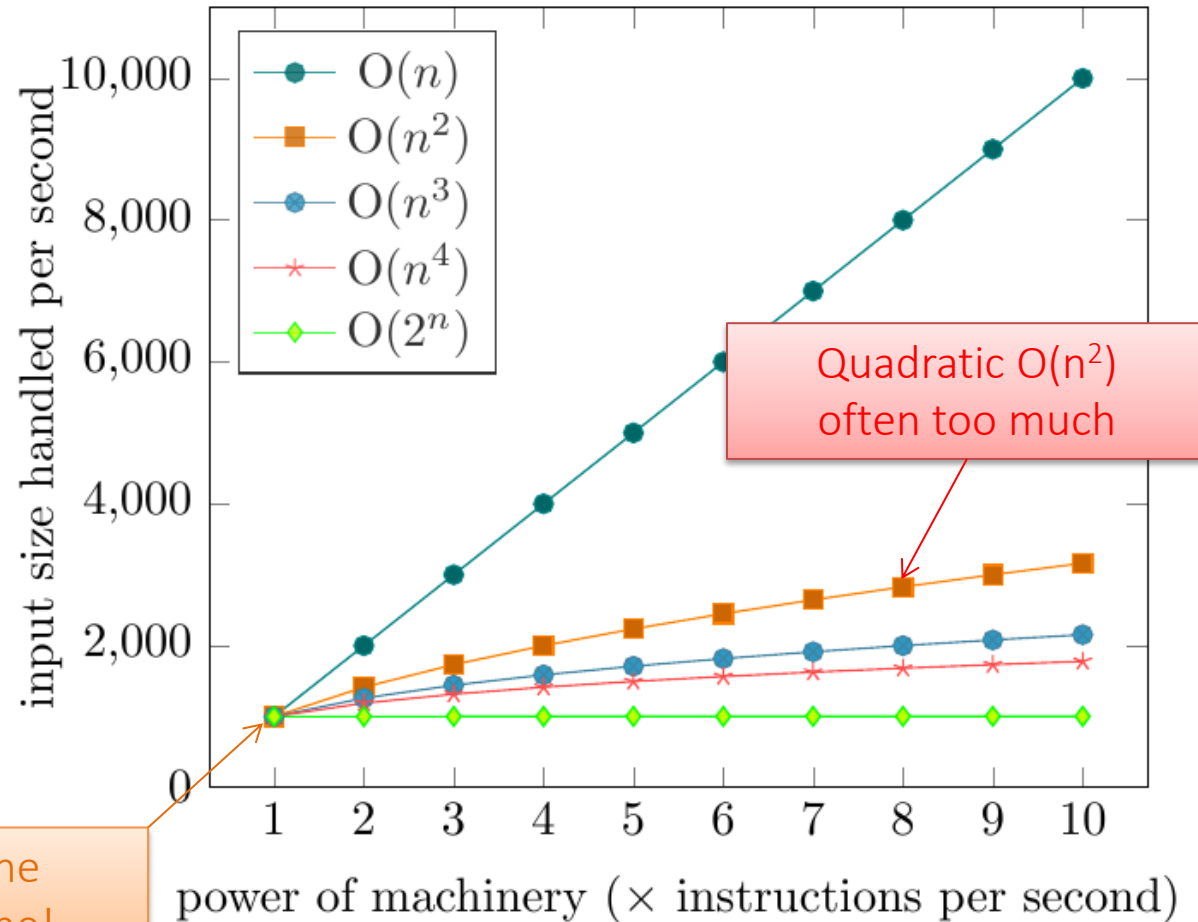
Scale is a Common Factor ...

I have an algorithm. ?

I have a machine that can process 1,000 input items in an hour.

If I buy a machine that is n times as powerful, how many input items can I process in an hour?

Depends on what the algorithm is!! !



Note: Not the same machine!

Scale is a Common Factor ...

- One machine that's n times as powerful?
- vs.*
- n machines that are equally as powerful?



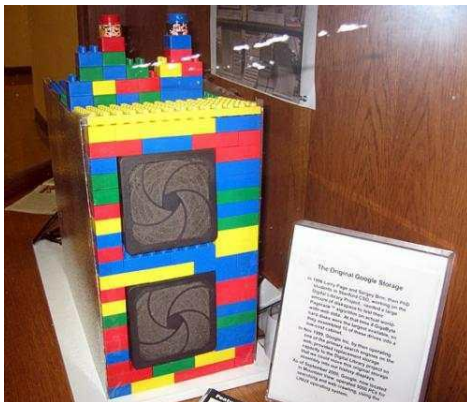
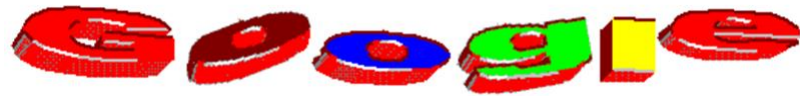
Scale is a Common Factor ...

- Data-intensive
 - Inexpensive algorithms / Large inputs
 - e.g., Google, Facebook, Twitter
- Compute-intensive
 - More expensive algorithms / Smaller inputs
 - e.g., climate simulations, chess games, combinatorials
- No black and white!

DISTRIBUTED COMPUTING ...

Distributed Computing

- Lots of data? Need more than one machine!
- Google ca. 1998:

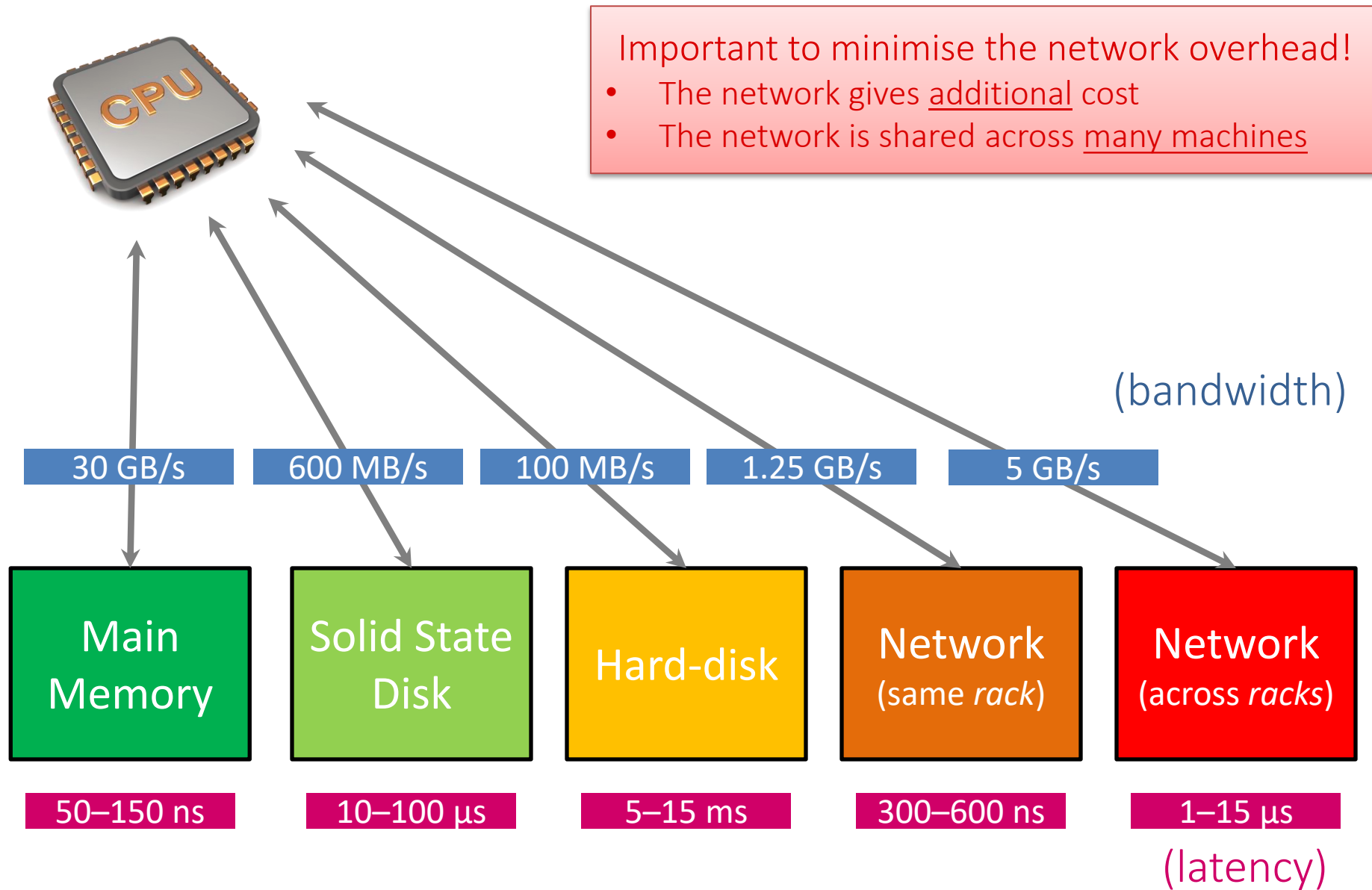


Distributed Computing

- Lots of data? Need more than one machine!
- Google ca. 2014:



Data Transport Costs (typical figures)



Data Placement

- Need to think carefully about where to put what data!

I have four machines to run a website. I have 10 million users. 

Each user has personal profile data, photos, friends and games.

How should I split the data up over the machines?

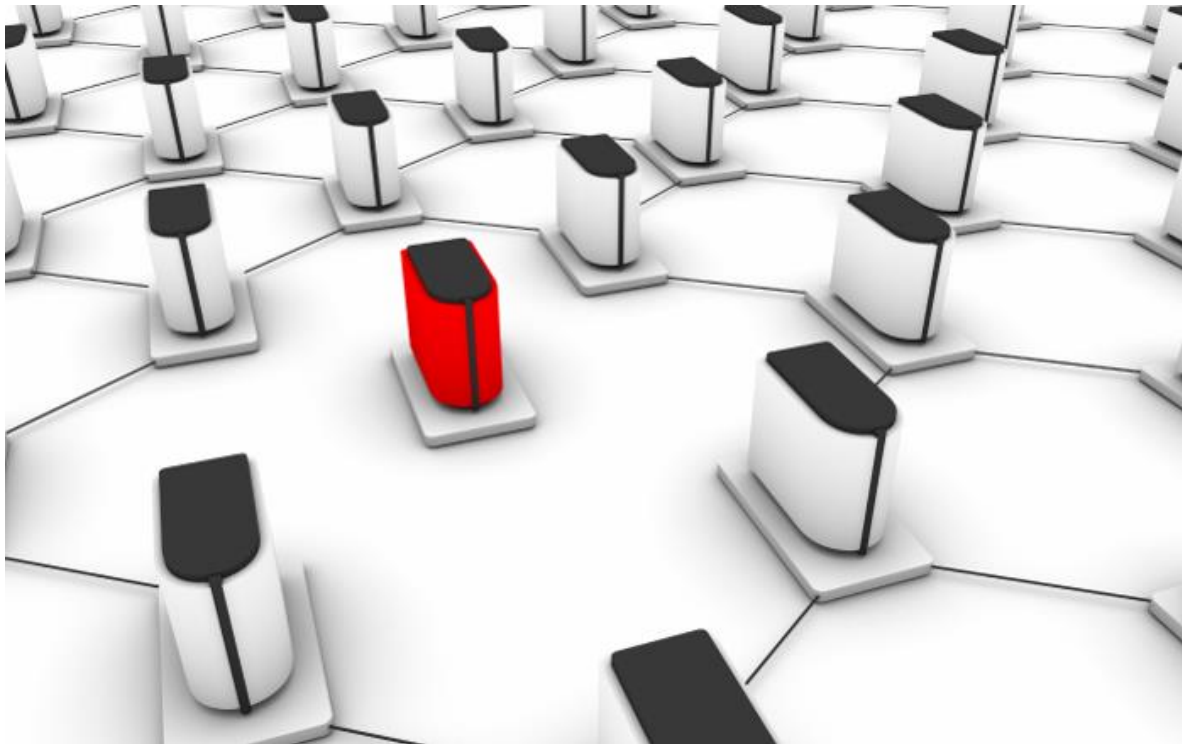
Depends on the application! 

But some general principles and design choices apply.



Network/Node Failures

- Need to think about failures!



Network/Node Failures

- Need to think (**even more!**) carefully about where to put what data!

I have four machines to run a website. I have 10 million users. 

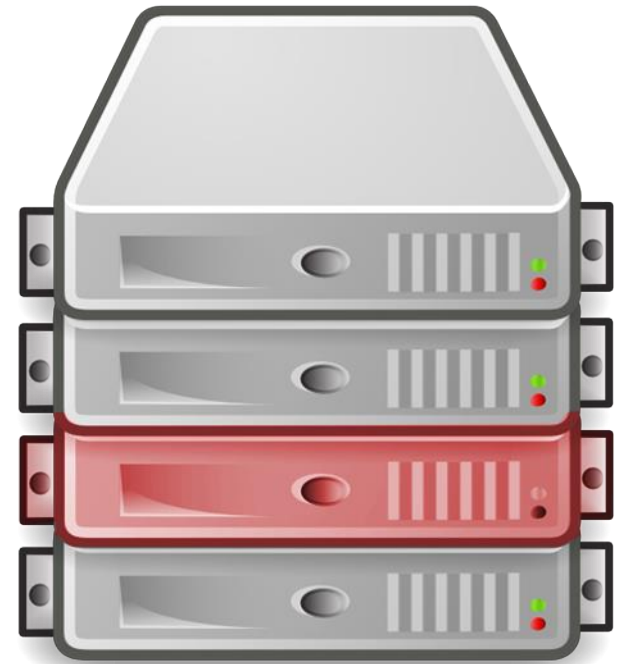
Each user has personal profile data, photos, friends and games.

How should I split the data up over the machines?

(Again) 

Depends on the application!

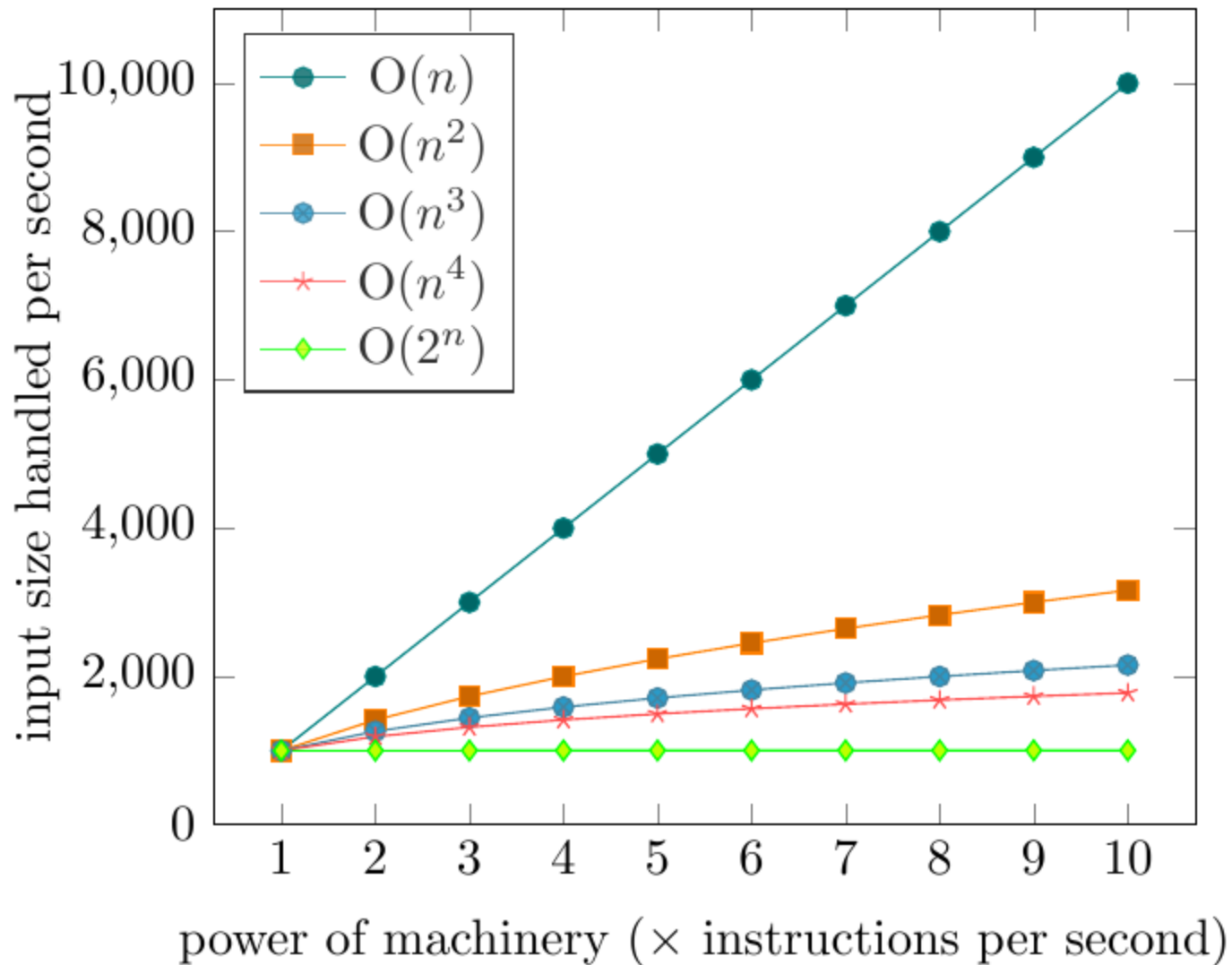
But some general principles and design choices apply.



Human Distributed Computation



Distribution Not Always Applicable!



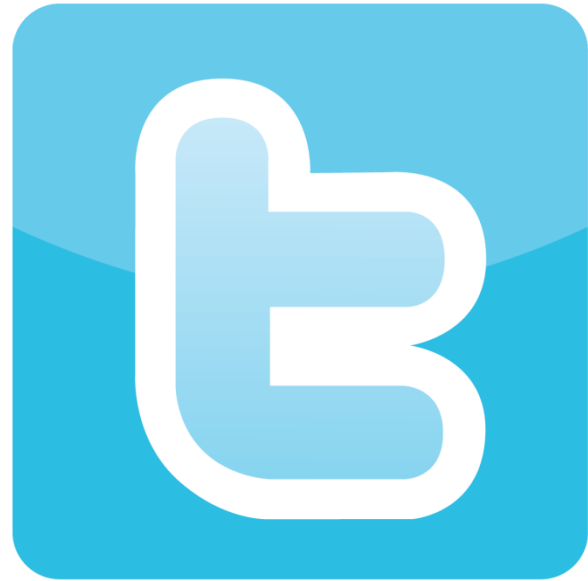
Distributed Development Difficult

- Distributed systems can be complex
- Multiple machines; need to take care of
 - Data in different locations
 - Logs and messages in different places
 - Different users with different priorities
 - Different network capabilities
 - Need to balance load!
 - Need to handle failures!
- Tasks may take a long time!
 - Bugs may not become apparent for hours
 - Lots of data = lots of counter-examples

Frameworks/Abstractions can Help

- For Distrib. Processing
- For Distrib. Storage





INSIDE TWITTER ...

Based on 2013 slides by Twitter lead architect: Raffi Krikorian



“Twitter Timelines at Scale”

Twitter Timeline

[Home](#) [Moments](#) [Notifications](#) [Messages](#) 

Search Twitter   [Tweet](#)

**leon**
@leyawn
TWEETS 11.3K FOLLOWING 714 FOLLOWERS 43K

United States Trends · [Change](#)
[#AskAlexa](#)
 Promoted by Amazon Echo
[#TheSuperBowl](#)
[Howard Dean](#)
[#ILoveYouZayn](#)
[#SelenaGomezLive](#)
[#ItsChineseNewYear](#)
[#sundaymotivation](#)
[Free Beer](#)
[Alexa Says](#)
[Katie Holmes](#)
[Every Vote Counts](#)

What's happening? 

Now viewing Top Tweets. [Switch to Most Recent Tweets?](#)

**jon hendren** @fart · 7h
the doritos corporation is skywriting over town for the super bowl. fools i already told you we are a [#FyunysFamily](#)
  17  117  [Top Tweet](#)

**demi adejuyigbe** @electrolemon · 1h
my mom just called me to say she doesn't think the halftime show was beyonce's best but she likes that coldplay guy. the polls are closed
  36  383 

Here are some Top Tweets you might enjoy.
[Refresh](#) · [View all](#)

**Fred Delicious** @Fred_Delicious · 9h
Accidentally glued myself to the ceiling again
  152  266  [Top Tweet](#)

**jomny sun** @jonnyson · 1h
great super bowl evreybody see u next year
  239  593  [Top Tweet](#)

**Twitter Small Biz** @TwitterSmallBiz · Jan 27
Start promoting your business on Twitter with a budget that works for you.


Who to follow · [Refresh](#) · [View all](#)
**Daniel S. Johnson** @linern... 
[Follow](#)
**Bill Maher**  @billmaher 
[Follow](#)
**Edward Snowden**  @Sno... 
[Follow](#)
[Find friends](#)

© 2016 Twitter [About](#) [Help](#) [Terms](#) [Privacy](#)
[Cookies](#) [Ads info](#) [Brand](#) [Blog](#) [Status](#) [Apps](#)
[Jobs](#) [Advertise](#) [Businesses](#) [Media](#)
[Developers](#)

Big Data at Twitter

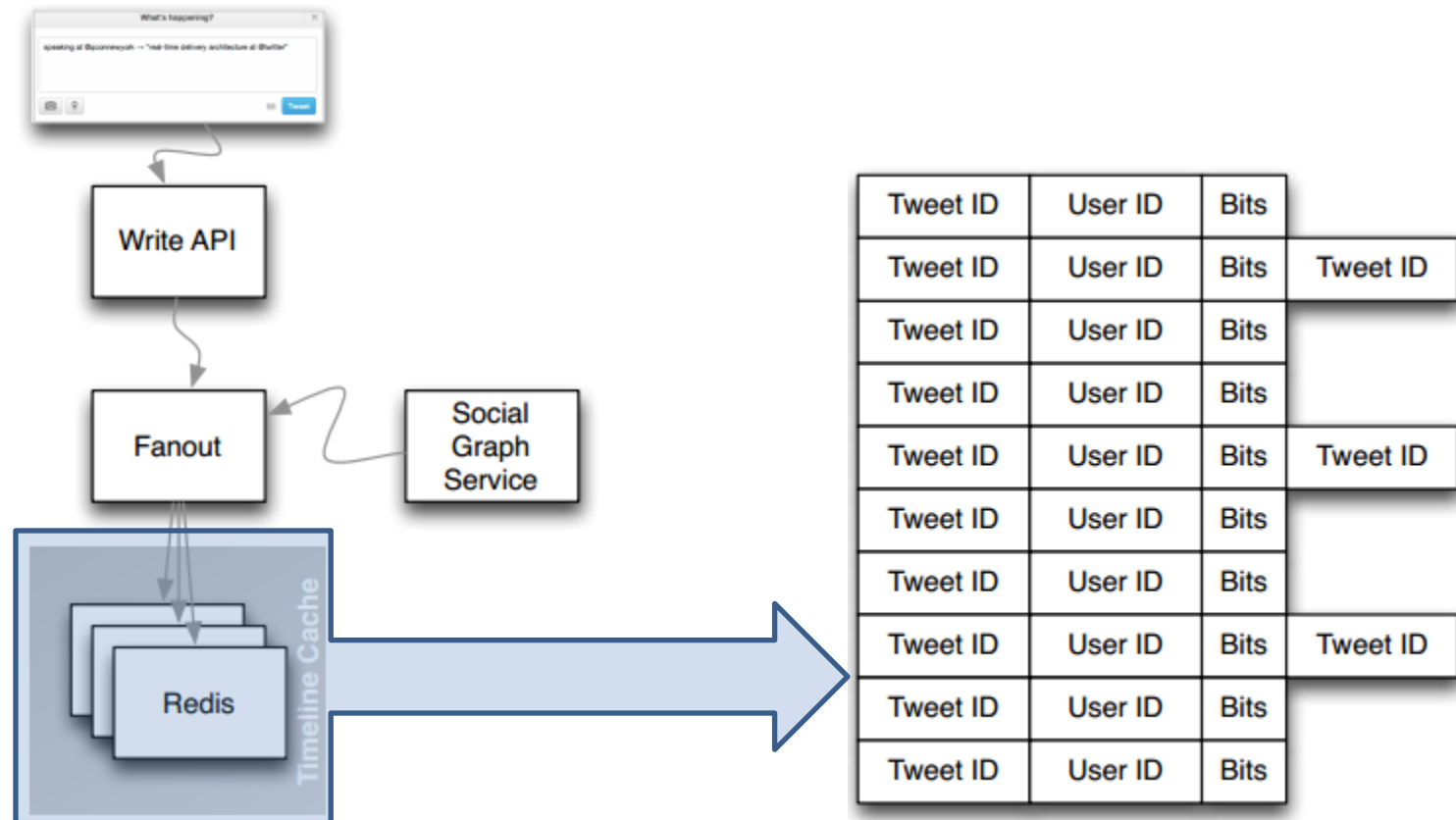
- 150 million active worldwide users
- 400 million tweets written per day
 - mean: 4,600 tweets/second
 - max: 150,000 tweets/second
- 300,000 queries/second for user timelines
- 6,000 queries/second for custom search

Which aspect is most important to optimise?



Supporting timelines: Write

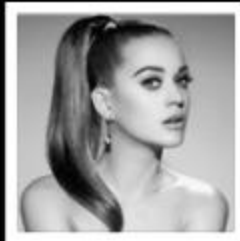
- mean: 4,000 tweets/second



High-fanout



@ladygaga ✓
31 million followers



@katyperry ✓
28 million followers



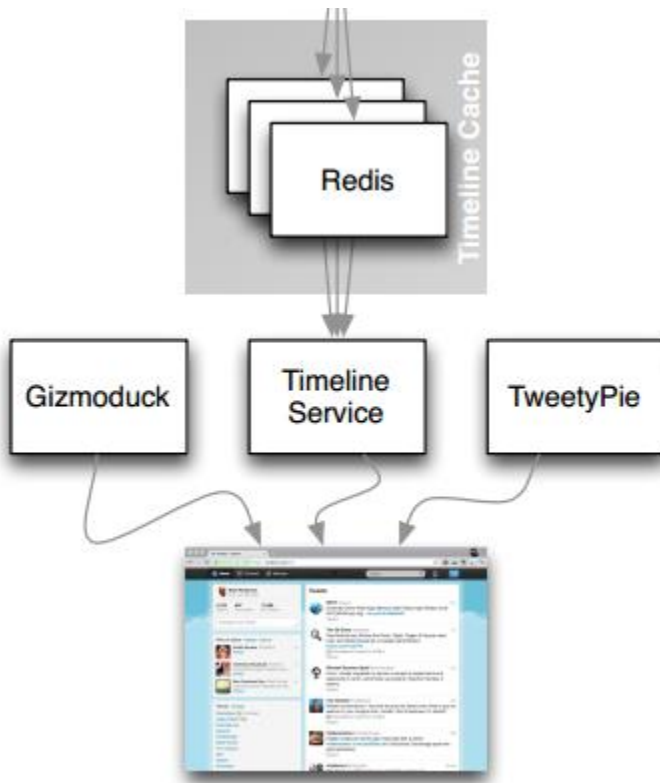
@justinbieber ✓
28 million followers



@barackobama ✓
23 million followers

Supporting timelines: Read

- 300,000 queries/second

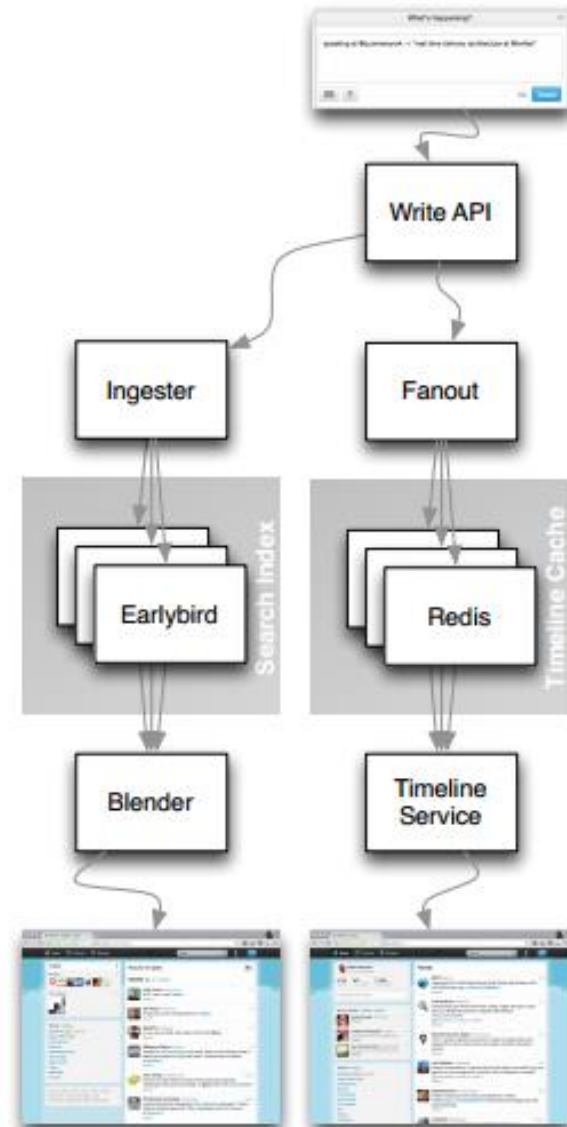


Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	Tweet ID
Tweet ID	User ID	Bits	
Tweet ID	User ID	Bits	

1ms @p50
4ms @p99

Supporting text search

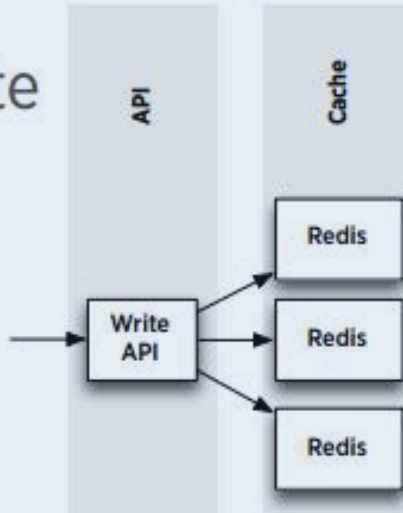
- Information retrieval
 - Earlybird: Lucene clone
 - Write once
 - Query many



Timeline vs. Search

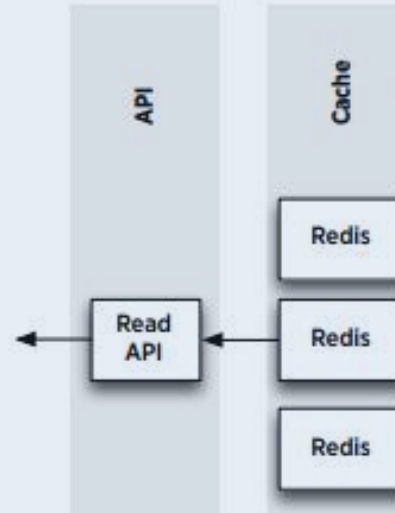
4,600 requests/sec

→ $O(n)$ write

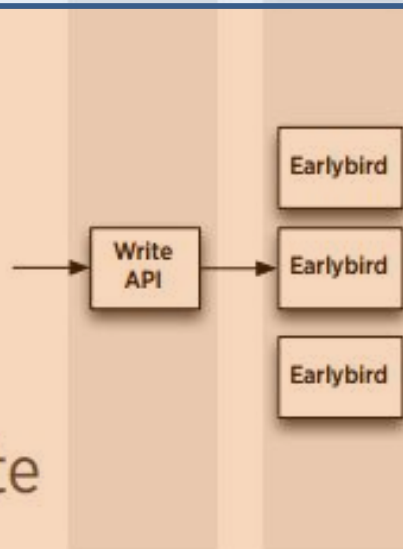


300,000 requests/sec

→ $O(1)$ read

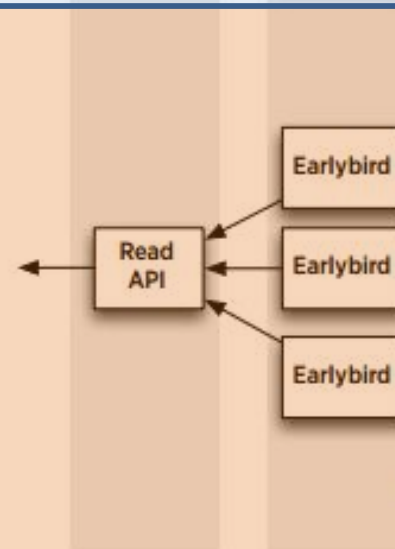


→ $O(1)$ write



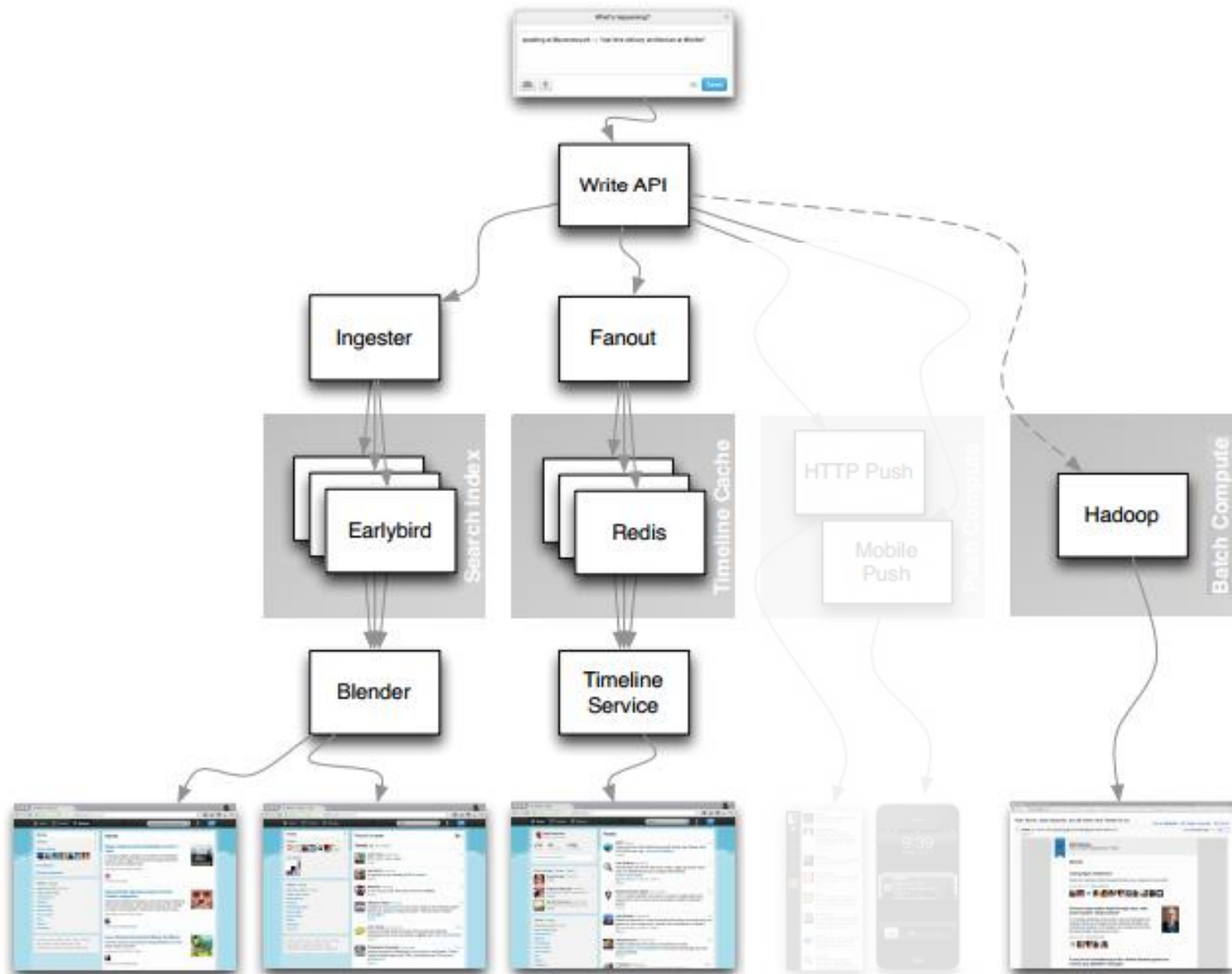
4,600 requests/sec

→ $O(n)$ read

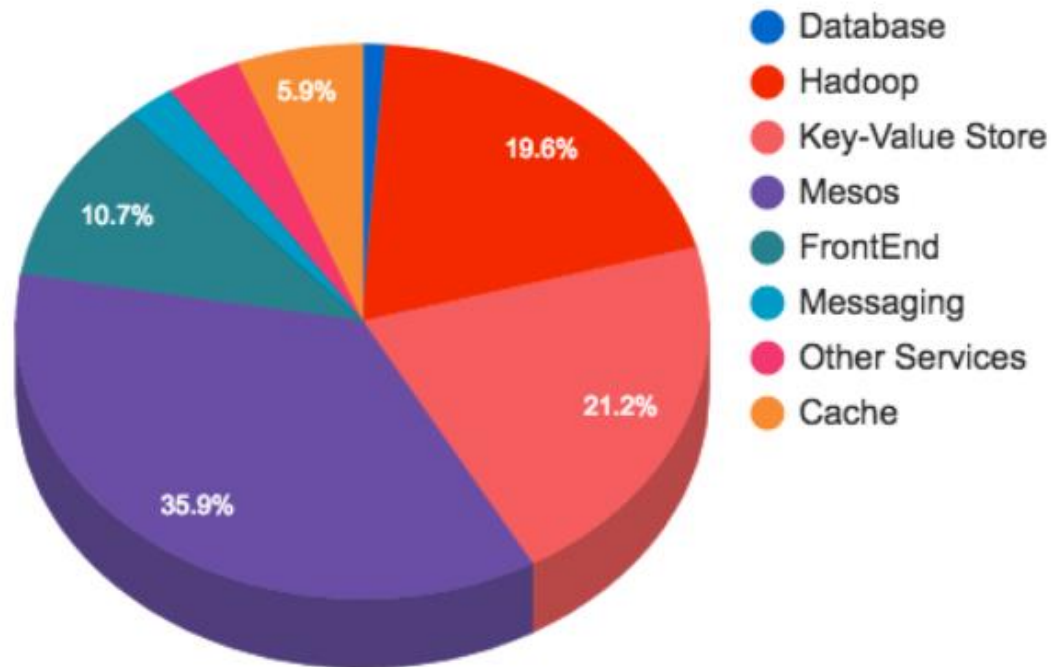


6,000 requests/sec

Twitter: Full architecture



Twitter en ~~2021~~ 2017?



https://blog.twitter.com/engineering/en_us/topics/infrastructure/2017/the-infrastructure-behind-twitter-scale.html

IN-MEMORY VS. DISK PROCESSING

Count words/phrases

INPUT: file (input text file), k (print top-k most frequent)

```
map = new Map()

for(word w: file)
    count = map.get(w)
    if(count is null)
        map.put(w,1)
    else
        map.put(w,count+1)

list = sortByValueDescending(map)
print(list[1,k])
```

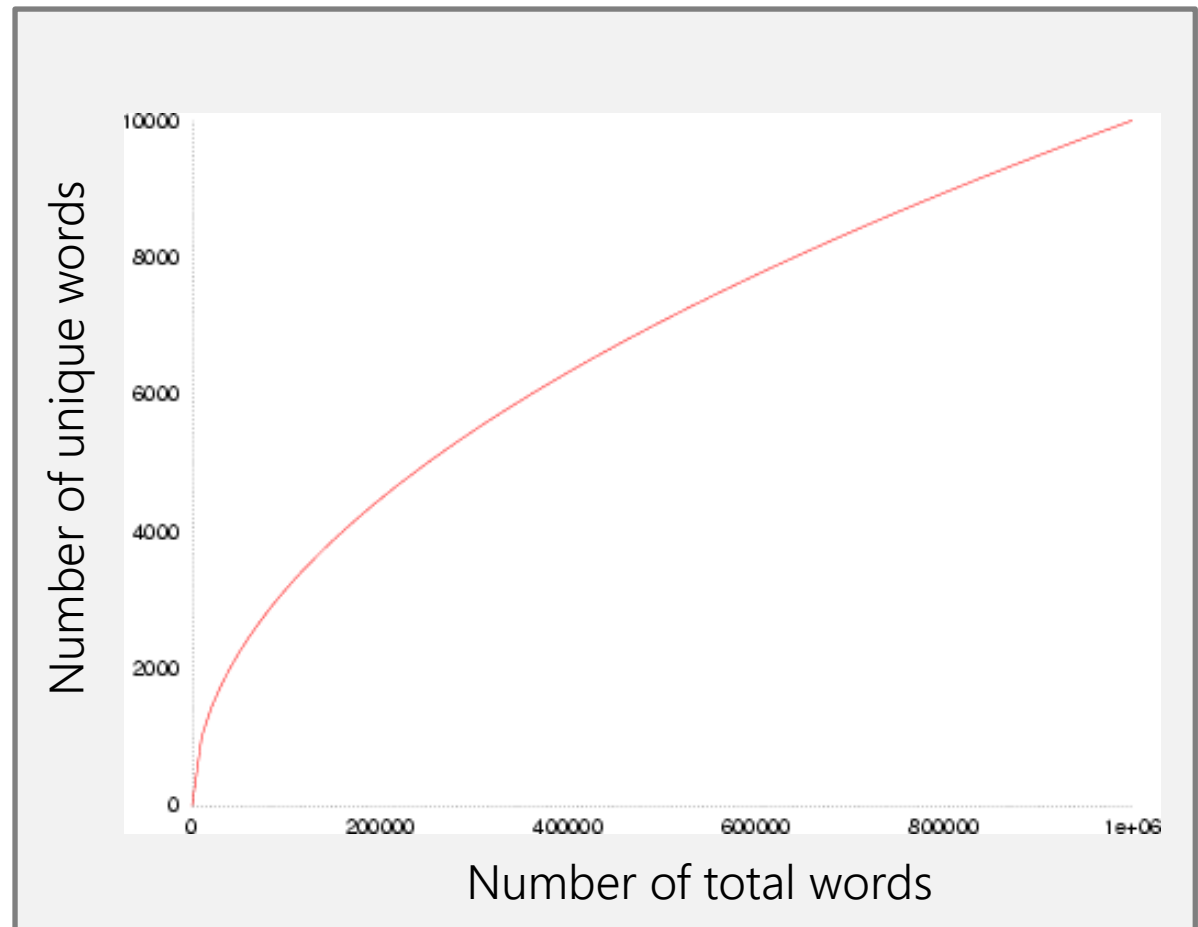
Any issues?



Count words in-memory

We can count words over very large corpora in memory

- Heap's law:



And if the phrases don't fit in memory?

What can we do then?



Count words/phrases on disk

INPUT: file (input text file), k (print top-k most frequent)

```
map = new Map()
```

```
for(word w: file)
```

```
    count = map.get(w)    ← random access
```

```
    if(count is null)
```

```
        map.put(w,1)    ← random access
```

```
    else
```

```
        map.put(w,count+1)    ← random access
```

```
list = sortByValueDescending(map)
```

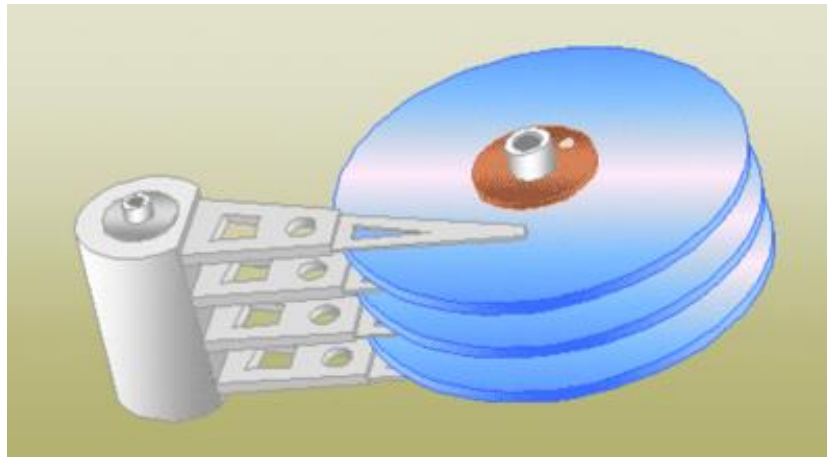
```
print(list[1,k])
```

Can we do the same
storing the map on-disk?



Physical disk arm

- Takes time to physically move the arm
 - Needed for random accesses
 - Around 10 ms seek time
 - About 3 hours to do one million seeks



Can we count words/phrases on-disk using more sequential access and less random access?

Order the words

tengo
que
aprender
más
español
tan
pronto
que
puedo
y
tengo
que
tomar
cada
oportunidad
para
practicar
como
ahora



ahora
aprender
cada
como
español
más
oportunidad
para
practicar
pronto
puedo
que
que
que
tan
tengo
tengo
tomar
y



ahora	1
aprender	1
cada	1
como	1
español	1
más	1
oportunidad	1
para	1
practicar	1
pronto	1
puedo	1
que	3
tan	1
tengo	2
tomar	1
y	1



que	3
tengo	2
ahora	1
aprender	1
cada	1
como	1
español	1
más	1
oportunidad	1
para	1
practicar	1
pronto	1
puedo	1
tan	1
tomar	1
y	1

How can we order the words on disk?

External Sort 1: Sort Batches

- Order the data in batches

Input (disk)
(Size: n)

es que
de la
por qué
de la
ha sido
no hay
de la
y de
ha sido
de la
así es
ha sido

Order (in memory)
(Batch size: b)



Intermediate output (disk)
($\lceil n/b \rceil$ batches)

de la
de la
es que
por qué

de la
ha sido
no hay
y de

así es
de la
ha sido
ha sido

External Sort 2: Merge-sort Batches

Intermediate output (disk)
($\lceil n/b \rceil$ batches)

de la
de la
es que
por qué

[1]

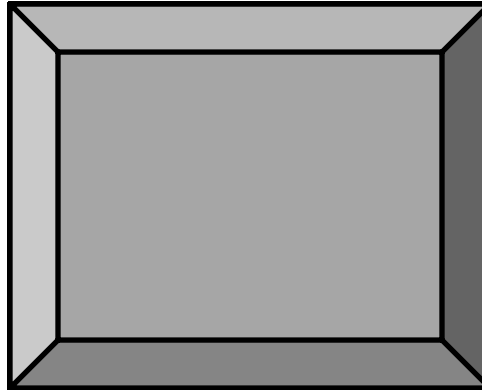
de la
ha sido
no hay
y de

[2]

así es
de la
ha sido
ha sido

[3]

Order (in memory)
(Size: $\lceil n/b \rceil$)



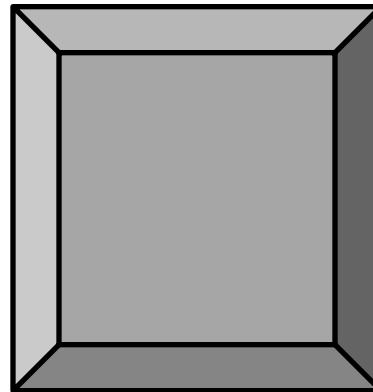
Output (disk)
(Size: n)

así es
de la
de la
de la
de la
es que
ha sido
ha sido
ha sido
no hay
por qué
y de

Count

así es
de la
de la
de la
de la
es que
ha sido
ha sido
ha sido
no hay
por qué
y de

If we want, we can
order again by
frequency using the
same method on-disk



así es,	1
de la,	4
es que,	1
ha sido,	3
no hay,	1
por qué,	1
y de,	1



Scale further?



ABOUT THE COURSE ...

What the Course Is/Is Not

- Data-intensive not compute-intensive
- Distributed tasks not networking
- Commodity hardware not supercomputers
- General methods not specific algorithms
- Practical methods with a little theory

What the Course Is

- Distributed Computing [1 week]
- Distributed Processing Frameworks [5 weeks]
- Information Retrieval [2 weeks]
- Distributed Databases [3 weeks]
- Projects [1–2 weeks]

Course Structure

- Mondays: Lecture
- Wednesdays: Lab
 - You can work in groups if you attend the session
 - Otherwise you must work alone
- Fridays: Auxiliar
 - Continuation of the labs
 - Resolve questions/doubts

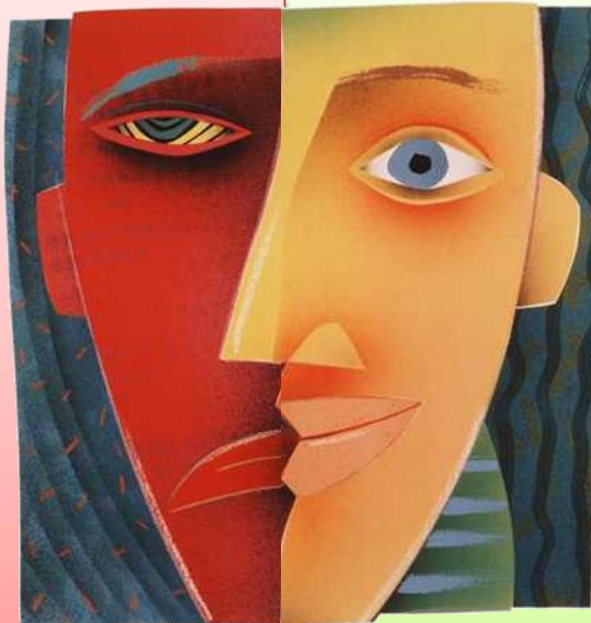
<http://aidanhogan.com/teaching/cc5212-1-2021/>

Course Marking

- 80% for Weekly Labs
 - 11 labs total
 - 4 labs will be obligatory
 - 4 best out of the remaining 7 labs will count
- 20% for Class Project

Assignments each week

Working in groups



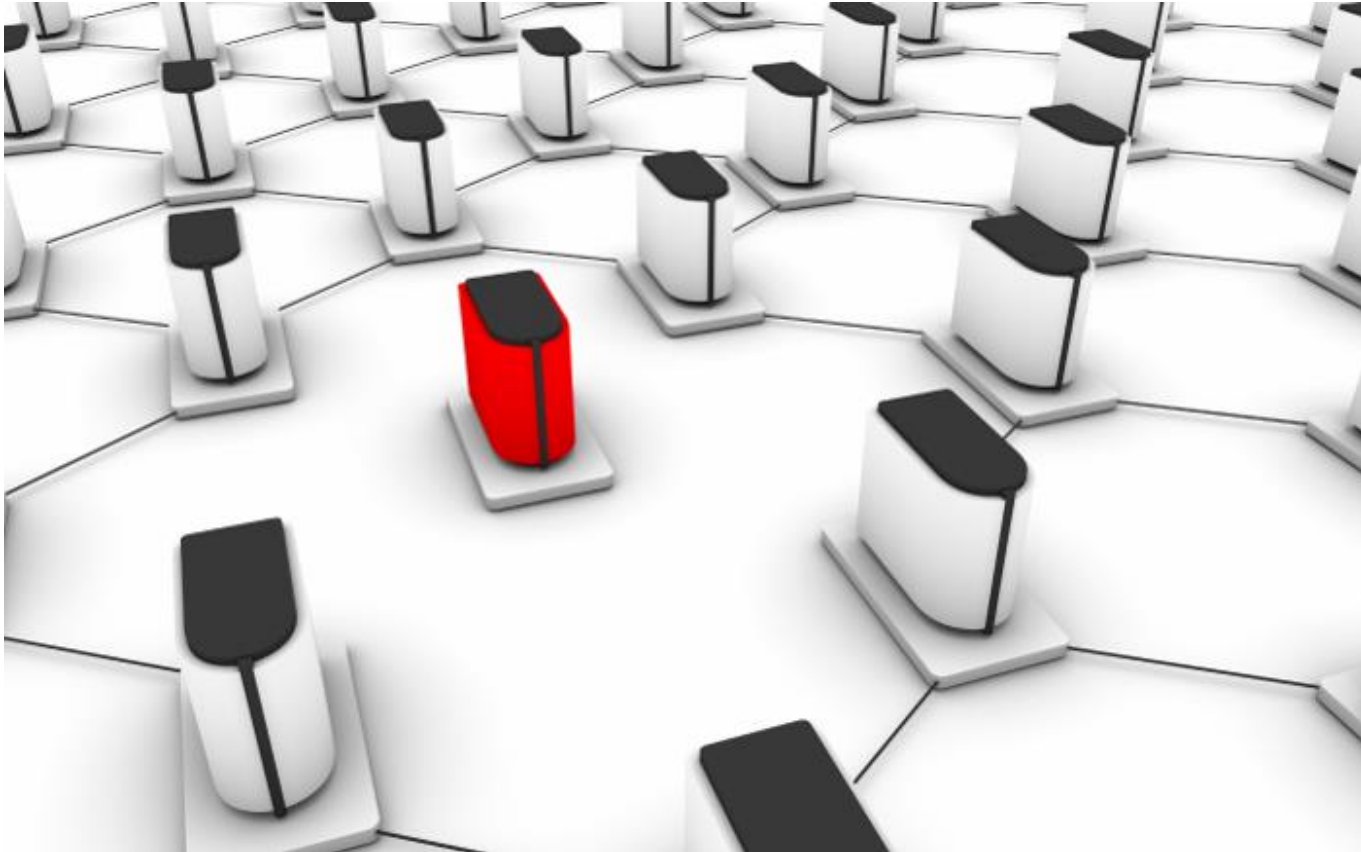
Hands-on each week!

Working in groups!

Outcomes!



Outcomes!



Outcomes!



Outcomes!





Questions?